# autogluon_each_location

November 8, 2023

## 1 Config

[45]:
```
# config

label = 'y'
metric = 'mean_absolute_error'
time_limit = 60*10
presets = "best_quality"#'best_quality'

do_drop_ds = True
# hour, dayofweek, dayofmonth, month, year
use_dt_attrs = []#["hour", "year"]
use_estimated_diff_attr = False
use_is_estimated_attr = True

drop_night_outliers = True
drop_null_outliers = False

# to_drop = ["snow_drift:idx", "snow_density:kgm3", "wind_speed_w_1000hPa:ms",␣
↪"dew_or_rime:idx", "prob_rime:p", "fresh_snow_12h:cm", "fresh_snow_24h:cm",␣
↪"wind_speed_u_10m:ms", "wind_speed_v_10m:ms", "snow_melt_10min:mm",␣
↪"rain_water:kgm2", "dew_point_2m:K", "precip_5min:mm", "absolute_humidity_2m:
↪gm3", "air_density_2m:kgm3"]#, "msl_pressure:hPa", "pressure_50m:hPa", ␣
↪"pressure_100m:hPa"]
to_drop = ["wind_speed_w_1000hPa:ms", "wind_speed_u_10m:ms", "wind_speed_v_10m:
↪ms"]

excluded_model_types = ['CAT', 'XGB', 'RF']

use_groups = False
n_groups = 8

# auto_stack = True
num_stack_levels = 0
num_bag_folds = None# 8
num_bag_sets = None#20
```

```
use_tune_data = True
use_test_data = True
#tune_and_test_length = 0.5 # 3 months from end
# holdout_frac = None
use_bag_holdout = True # Enable this if there is a large gap between score_val␣
↪and score_test in stack models.

sample_weight = None#'sample_weight' #None
weight_evaluation = False#
sample_weight_estimated = 1
sample_weight_may_july = 1

run_analysis = False

shift_predictions_by_average_of_negatives_then_clip = False
clip_predictions = True
shift_predictions = False
```

## 2 Loading and preprocessing

[46]:
```
import pandas as pd
import numpy as np



import warnings
warnings.filterwarnings("ignore")


def feature_engineering(X):
    # shift all columns with "1h" in them by 1 hour, so that for index 16:00,␣
↪we have the values from 17:00
    # but only for the columns with "1h" in the name
    #X_shifted = X.filter(regex="\dh").shift(-1, axis=1)
    #print(f"Number of columns with 1h in name: {X_shifted.columns}")


    columns = ['clear_sky_energy_1h:J', 'diffuse_rad_1h:J', 'direct_rad_1h:J',
               'fresh_snow_12h:cm', 'fresh_snow_1h:cm', 'fresh_snow_24h:cm',
               'fresh_snow_3h:cm', 'fresh_snow_6h:cm']

    # Filter rows where index.minute == 0
    X_shifted = X[X.index.minute == 0][columns].copy()

    # Create a set for constant-time lookup
    index_set = set(X.index)
```

```python
    # Vectorized time shifting
    one_hour = pd.Timedelta('1 hour')
    shifted_indices = X_shifted.index + one_hour
    X_shifted.loc[shifted_indices.isin(index_set)] = X.
↪loc[shifted_indices[shifted_indices.isin(index_set)]][columns]

    # set last row to same as second last row
    X_shifted.iloc[-1] = X_shifted.iloc[-2]

    # Count
    count1 = len(shifted_indices[shifted_indices.isin(index_set)])
    count2 = len(X_shifted) - count1

    print("COUNT1", count1)
    print("COUNT2", count2)

    # Rename columns
    X_old_unshifted = X_shifted.copy()
    X_old_unshifted.columns = [f"{col}_not_shifted" for col in X_old_unshifted.
↪columns]

    date_calc = None
    # If 'date_calc' is present, handle it
    if 'date_calc' in X.columns:
        date_calc = X[X.index.minute == 0]['date_calc']




    # resample to hourly
    print("index: ", X.index[0])
    X = X.resample('H').mean()
    print("index AFTER: ", X.index[0])

    X[columns] = X_shifted[columns]
    #X[X_old_unshifted.columns] = X_old_unshifted

    if date_calc is not None:
        X['date_calc'] = date_calc

    return X




def fix_X(X, name):
```

```python
    # Convert 'date_forecast' to datetime format and replace original column
    ↪with 'ds'
    X['ds'] = pd.to_datetime(X['date_forecast'])
    X.drop(columns=['date_forecast'], inplace=True, errors='ignore')
    X.sort_values(by='ds', inplace=True)
    X.set_index('ds', inplace=True)


    X = feature_engineering(X)

    return X




def handle_features(X_train_observed, X_train_estimated, X_test, y_train):
    X_train_observed = fix_X(X_train_observed, "X_train_observed")
    X_train_estimated = fix_X(X_train_estimated, "X_train_estimated")
    X_test = fix_X(X_test, "X_test")


    if weight_evaluation:
        # add sample weights, which are 1 for observed and 3 for estimated
        X_train_observed["sample_weight"] = 1
        X_train_estimated["sample_weight"] = sample_weight_estimated
        X_test["sample_weight"] = sample_weight_estimated


    y_train['ds'] = pd.to_datetime(y_train['time'])
    y_train.drop(columns=['time'], inplace=True)
    y_train.sort_values(by='ds', inplace=True)
    y_train.set_index('ds', inplace=True)

    return X_train_observed, X_train_estimated, X_test, y_train





def preprocess_data(X_train_observed, X_train_estimated, X_test, y_train,
↪location):
    # convert to datetime
    X_train_observed, X_train_estimated, X_test, y_train =
↪handle_features(X_train_observed, X_train_estimated, X_test, y_train)

    if use_estimated_diff_attr:
        X_train_observed["estimated_diff_hours"] = 0
        X_train_estimated["estimated_diff_hours"] = (X_train_estimated.index -
↪pd.to_datetime(X_train_estimated["date_calc"])).dt.total_seconds() / 3600
```

```
        X_test["estimated_diff_hours"] = (X_test.index - pd.
↪to_datetime(X_test["date_calc"])).dt.total_seconds() / 3600

        X_train_estimated["estimated_diff_hours"] =␣
↪X_train_estimated["estimated_diff_hours"].astype('int64')
        # the filled once will get dropped later anyways, when we drop y nans
        X_test["estimated_diff_hours"] = X_test["estimated_diff_hours"].
↪fillna(-50).astype('int64')

    if use_is_estimated_attr:
        X_train_observed["is_estimated"] = 0
        X_train_estimated["is_estimated"] = 1
        X_test["is_estimated"] = 1


    # drop date_calc
    X_train_estimated.drop(columns=['date_calc'], inplace=True)
    X_test.drop(columns=['date_calc'], inplace=True)


    y_train["y"] = y_train["pv_measurement"].astype('float64')
    y_train.drop(columns=['pv_measurement'], inplace=True)
    X_train = pd.concat([X_train_observed, X_train_estimated])


    # clip all y values to 0 if negative
    y_train["y"] = y_train["y"].clip(lower=0)

    X_train = pd.merge(X_train, y_train, how="inner", left_index=True,␣
↪right_index=True)

    # print number of nans in y
    print(f"Number of nans in y: {X_train['y'].isna().sum()}")

    print(f"Size of estimated after dropping nans:␣
↪{len(X_train[X_train['is_estimated']==1].dropna(subset=['y']))}")


    X_train["location"] = location
    X_test["location"] = location

    return X_train, X_test
# Define locations
locations = ['A', 'B', 'C']

X_trains = []
X_tests = []
```

```python
# Loop through locations
for loc in locations:
    print(f"Processing location {loc}...")
    # Read target training data
    y_train = pd.read_parquet(f'{loc}/train_targets.parquet')

    # Read estimated training data and add location feature
    X_train_estimated = pd.read_parquet(f'{loc}/X_train_estimated.parquet')

    # Read observed training data and add location feature
    X_train_observed= pd.read_parquet(f'{loc}/X_train_observed.parquet')

    # Read estimated test data and add location feature
    X_test_estimated = pd.read_parquet(f'{loc}/X_test_estimated.parquet')

    # Preprocess data
    X_train, X_test = preprocess_data(X_train_observed, X_train_estimated,␣
↪X_test_estimated, y_train, loc)

    X_trains.append(X_train)
    X_tests.append(X_test)

# Concatenate all data and save to csv
X_train = pd.concat(X_trains)
X_test = pd.concat(X_tests)
```

```
Processing location A…
COUNT1 29667
COUNT2 1
index:  2019-06-02 22:00:00
index AFTER:  2019-06-02 22:00:00
COUNT1 4392
COUNT2 2
index:  2022-10-28 22:00:00
index AFTER:  2022-10-28 22:00:00
COUNT1 702
COUNT2 18
index:  2023-05-01 00:00:00
index AFTER:  2023-05-01 00:00:00
Number of nans in y: 0
Size of estimated after dropping nans: 4418
Processing location B…
COUNT1 29232
COUNT2 1
index:  2019-01-01 00:00:00
index AFTER:  2019-01-01 00:00:00
COUNT1 4392
COUNT2 2
```

```
index:  2022-10-28 22:00:00
index AFTER:  2022-10-28 22:00:00
COUNT1 702
COUNT2 18
index:  2023-05-01 00:00:00
index AFTER:  2023-05-01 00:00:00
Number of nans in y: 4
Size of estimated after dropping nans: 3625
Processing location C…
COUNT1 29206
COUNT2 1
index:  2019-01-01 00:00:00
index AFTER:  2019-01-01 00:00:00
COUNT1 4392
COUNT2 2
index:  2022-10-28 22:00:00
index AFTER:  2022-10-28 22:00:00
COUNT1 702
COUNT2 18
index:  2023-05-01 00:00:00
index AFTER:  2023-05-01 00:00:00
Number of nans in y: 6059
Size of estimated after dropping nans: 2954
```

## 2.1 Feature enginering

### 2.1.1 Remove anomalies

[47]:
```
import numpy as np
import pandas as pd


# loop thorugh x train[y], keep track of streaks of same values and replace␣
↪them with nan if they are too long
# also replace nan with 0

import numpy as np

def replace_streaks_with_nan(df, max_streak_length, column="y"):
    for location in df["location"].unique():
        x = df[df["location"] == location][column].copy()

        last_val = None
        streak_length = 1
        streak_indices = []
        allowed = [0]
        found_streaks = {}
```

```
        for idx in x.index:
            value = x[idx]
            # if location == "B":
            #     continue

            if value == last_val and value not in allowed:
                streak_length += 1
                streak_indices.append(idx)
            else:
                streak_length = 1
                last_val = value
                streak_indices.clear()

            if streak_length > max_streak_length:
                found_streaks[value] = streak_length

                for streak_idx in streak_indices:
                    x[idx] = np.nan
                streak_indices.clear()  # clear after setting to NaN to avoid␣
 ↪setting multiple times
        df.loc[df["location"] == location, column] = x

        print(f"Found streaks for location {location}: {found_streaks}")

    return df


# deep copy of X_train into x_copy
X_train = replace_streaks_with_nan(X_train.copy(), 3, "y")
```

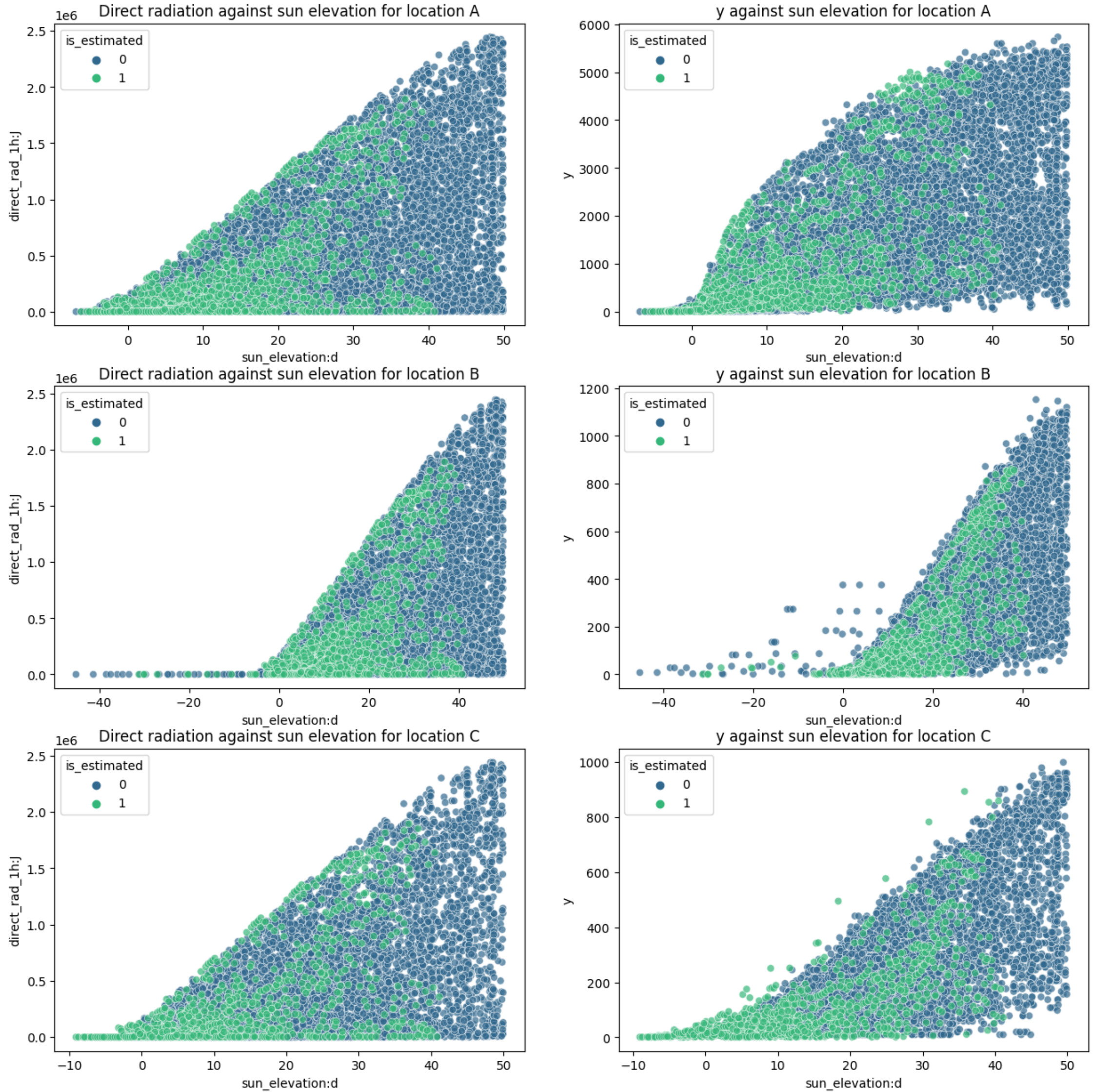
```
Found streaks for location A: {}
Found streaks for location B: {3.45: 28, 6.9: 7, 12.9375: 5, 13.8: 8, 276.0: 78,
18.975: 58, 0.8625: 4, 118.1625: 33, 34.5: 11, 183.7125: 1058, 87.1125: 7,
79.35: 34, 7.7625: 12, 27.6: 448, 273.41249999999997: 72, 264.78749999999997:
55, 169.05: 33, 375.1875: 56, 314.8125: 66, 76.7625: 10, 135.4125: 216, 81.9375:
202, 2.5875: 12, 81.075: 210}
Found streaks for location C: {9.8: 4, 29.400000000000002: 4, 19.6: 4}
```

[48]:
```
# print num rows
temprows = len(X_train)
X_train.dropna(subset=['y', 'direct_rad_1h:J', 'diffuse_rad_1h:J'],␣
 ↪inplace=True)
print("Dropped rows: ", temprows - len(X_train))
```

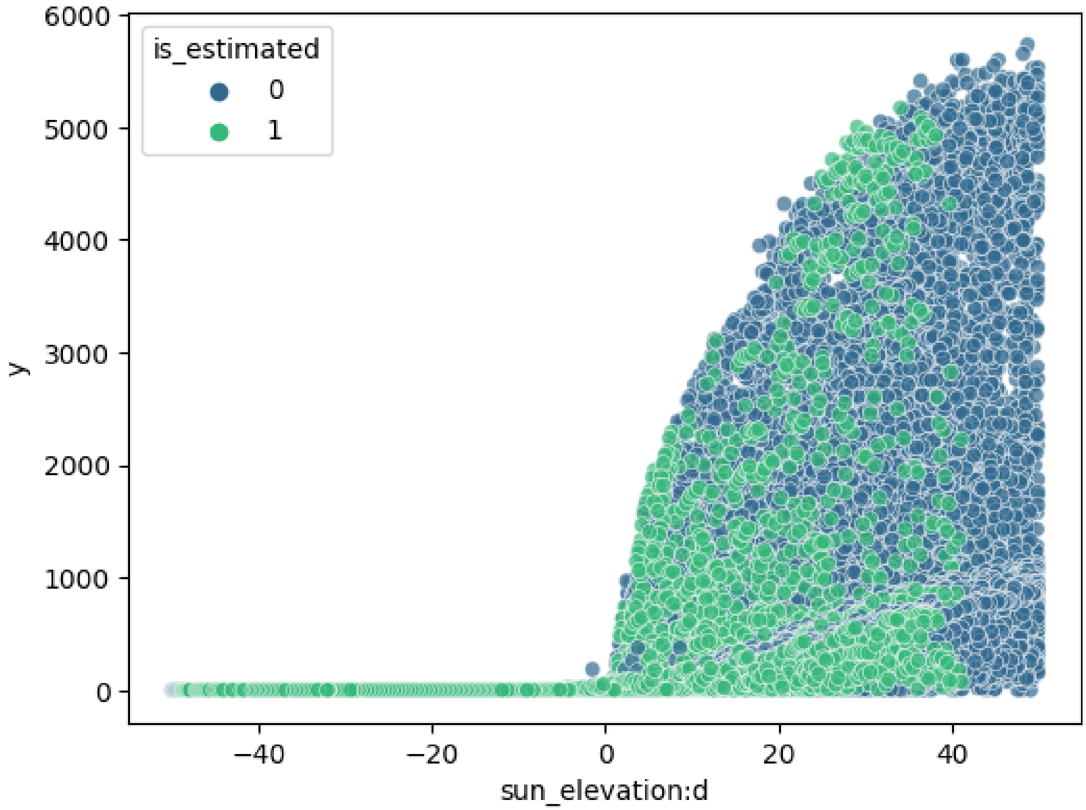
```
Dropped rows:  9293
```

[49]:
```
import matplotlib.pyplot as plt
import seaborn as sns
```

```python
# Filter out rows where y == 0
temp = X_train[X_train["y"] != 0]

# Plotting
fig, axes = plt.subplots(len(locations), 2, figsize=(15, 5 * len(locations)))

for idx, location in enumerate(locations):
    sns.scatterplot(ax=axes[idx][0], data=temp[temp["location"] == location],␣
 ↪x="sun_elevation:d", y="direct_rad_1h:J", hue="is_estimated",␣
 ↪palette="viridis", alpha=0.7)
    axes[idx][0].set_title(f"Direct radiation against sun elevation for␣
 ↪location {location}")

    sns.scatterplot(ax=axes[idx][1], data=temp[temp["location"] == location],␣
 ↪x="sun_elevation:d", y="y", hue="is_estimated", palette="viridis", alpha=0.7)
    axes[idx][1].set_title(f"y against sun elevation for location {location}")

# plt.tight_layout()
# plt.show()
```

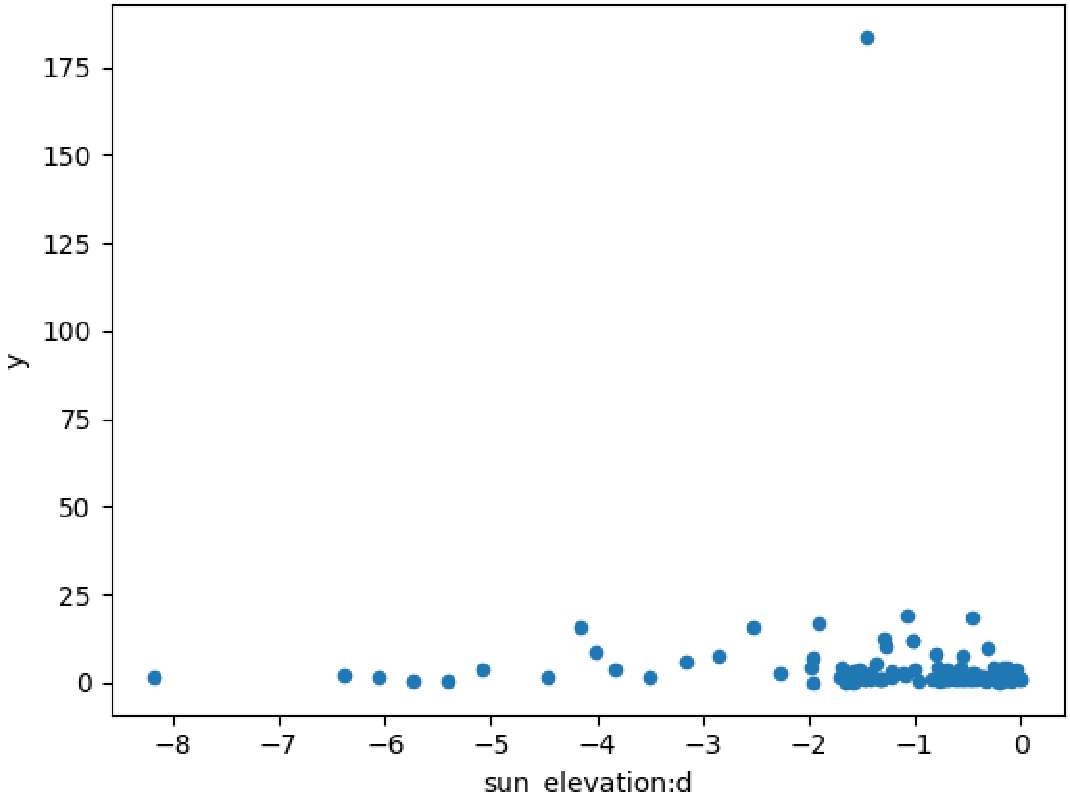



[50]:
```
thresh = 0.1

# Update "y" values to NaN if they don't meet the criteria
mask = (X_train["direct_rad_1h:J"] <= thresh) & (X_train["diffuse_rad_1h:J"] <=
 ↪thresh) & (X_train["y"] >= 0.1)
if drop_night_outliers:
    X_train.loc[mask, "y"] = np.nan

# Plot using sns scatterplot
sns.scatterplot(data=X_train, x="sun_elevation:d", y="y", hue="is_estimated",
 ↪palette="viridis", alpha=0.7)
plt.show()
```




[51]:
```
# location B count number of rows with y > 0 and sun_elevation:d < 0

condition = (X_train["location"] == "B") & (X_train["y"] > 0) &␣
↪(X_train["sun_elevation:d"] < 0)
bad = X_train[condition]

bad.plot.scatter(x="sun_elevation:d", y="y")
```

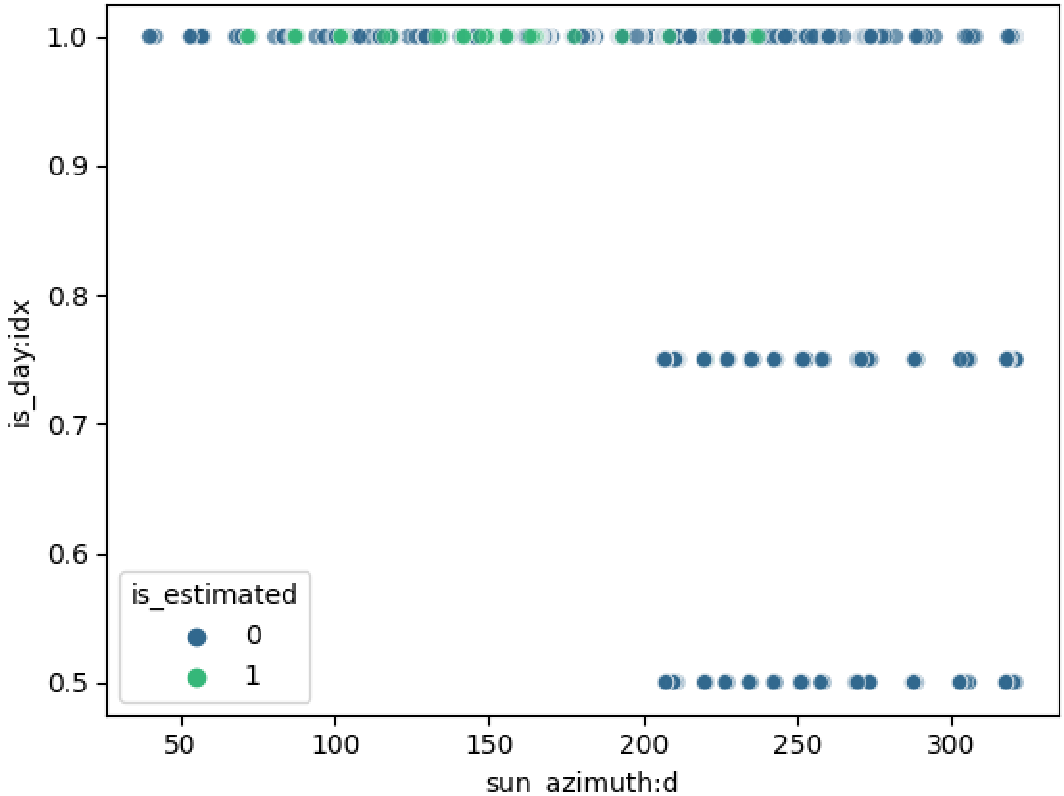
[51]: <AxesSubplot: xlabel='sun_elevation:d', ylabel='y'>



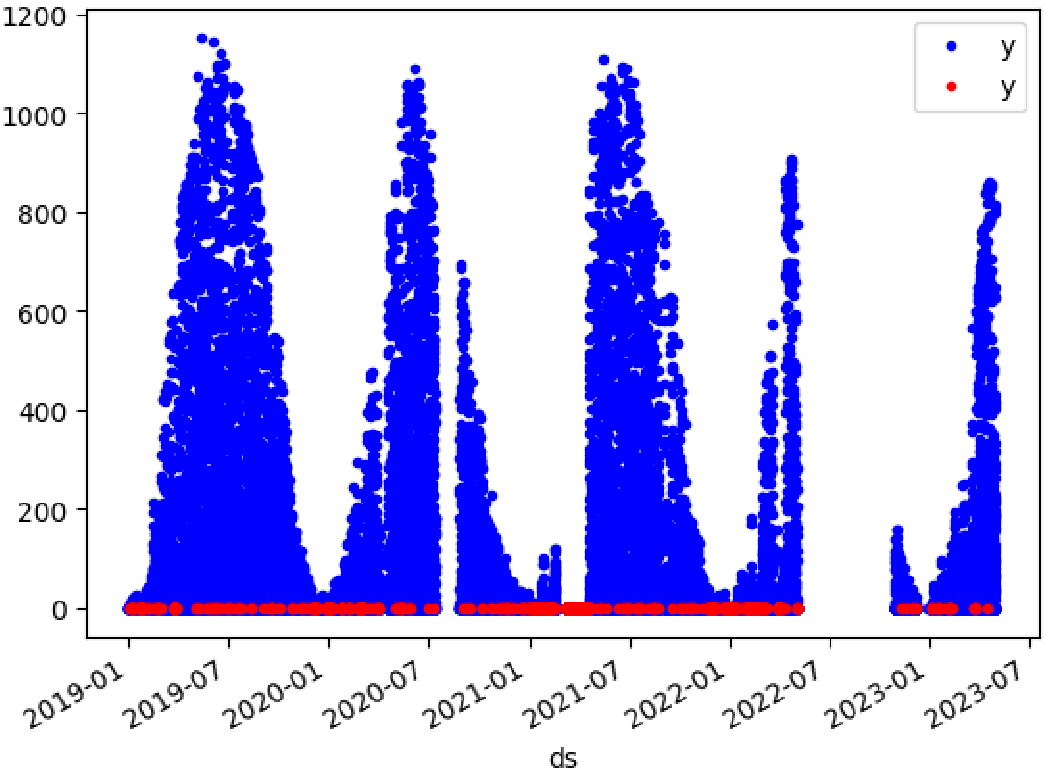

[52]:
```
# set y to nan where y is 0, but direct_rad_1h:J or diffuse_rad_1h:J are > 0␣
↪(or some threshold)
threshold_direct = X_train["direct_rad_1h:J"].max() * 0.01
threshold_diffuse = X_train["diffuse_rad_1h:J"].max() * 0.01
print(f"Threshold direct: {threshold_direct}")
print(f"Threshold diffuse: {threshold_diffuse}")

mask = (X_train["y"] == 0) & ((X_train["direct_rad_1h:J"] > threshold_direct) |␣
↪(X_train["diffuse_rad_1h:J"] > threshold_diffuse)) & (X_train["sun_elevation:
↪d"] > 0) & (X_train["fresh_snow_24h:cm"] < 6) & (X_train[['fresh_snow_12h:
↪cm', 'fresh_snow_1h:cm',  'fresh_snow_3h:cm', 'fresh_snow_6h:cm']].
↪sum(axis=1) == 0)
print(len(X_train[mask]))

#print(X_train[mask][[x for x in X_train.columns if "snow" in x]])

# show plot where mask is true
#sns.scatterplot(data=X_train[mask], x="sun_elevation:d", y="y",␣
↪hue="is_estimated", palette="viridis", alpha=0.7)
```

```python
sns.scatterplot(data=X_train[mask], x="sun_azimuth:d", y="is_day:idx",␣
↪hue="is_estimated", palette="viridis", alpha=0.7)
plt.show()

#sns.scatterplot(data=X_train[mask], x="fresh_snow_24h:cm",␣
↪y="total_cloud_cover:p", hue="is_estimated", palette="viridis", alpha=0.7)


# plot X_train["y"], but with another color where mask is true (only location B)
fig, ax = plt.subplots()
X_train[X_train["location"] == "B"].plot(y="y", ax=ax, style='.', color='b')
# now scatter plot of mask and b
X_train[(X_train["location"] == "B") & mask].plot(y="y", ax=ax, style='.',␣
↪color='r')


#X_train[(X_train["location"] == "B") & mask].plot(y="y", color='r')


# set y to nan where mask
if drop_null_outliers:
    X_train.loc[mask, "y"] = np.nan

# show how many rows for each location, and for estimated and not estimated
X_train[mask].groupby(["location", "is_estimated"]).count()["direct_rad_1h:J"]
```

```
Threshold direct: 24458.97
Threshold diffuse: 11822.505000000001
2599
```




```
[52]: location  is_estimated
      A         0                 87
                1                 10
      B         0               1250
                1                 32
      C         0               1174
                1                 46
      Name: direct_rad_1h:J, dtype: int64
```




[53]:
```
# print num rows
temprows = len(X_train)
X_train.dropna(subset=['y', 'direct_rad_1h:J', 'diffuse_rad_1h:J'],␣
 ↪inplace=True)
print("Dropped rows: ", temprows - len(X_train))
```

```
Dropped rows:  1876
```

### 2.1.2 Other stuff

[54]:
```
import numpy as np
import pandas as pd

for attr in use_dt_attrs:
    X_train[attr] = getattr(X_train.index, attr)
    X_test[attr] = getattr(X_test.index, attr)

#print(X_train.head())
```

```
# If the "sample_weight" column is present and weight_evaluation is True,␣
↪multiply sample_weight with sample_weight_may_july if the ds is between␣
↪05-01 00:00:00 and 07-03 23:00:00, else add sample_weight as a column to␣
↪X_train
if weight_evaluation:
    if "sample_weight" not in X_train.columns:
        X_train["sample_weight"] = 1

    X_train.loc[((X_train.index.month >= 5) & (X_train.index.month <= 6)) |␣
↪((X_train.index.month == 7) & (X_train.index.day <= 3)), "sample_weight"] *=␣
↪sample_weight_may_july


print(X_train.iloc[200])
print(X_train[((X_train.index.month >= 5) & (X_train.index.month <= 6)) |␣
↪((X_train.index.month == 7) & (X_train.index.day <= 3))].head(1))



if use_groups:
    # fix groups for cross validation
    locations = X_train['location'].unique()  # Assuming 'location' is the name␣
↪of the column representing locations

    grouped_dfs = []  # To store data frames split by location

    # Loop through each unique location
    for loc in locations:
        loc_df = X_train[X_train['location'] == loc]

        # Sort the DataFrame for this location by the time column
        loc_df = loc_df.sort_index()

        # Calculate the size of each group for this location
        group_size = len(loc_df) // n_groups

        # Create a new 'group' column for this location
        loc_df['group'] = np.repeat(range(n_groups),␣
↪repeats=[group_size]*(n_groups-1) + [len(loc_df) - group_size*(n_groups-1)])

        # Append to list of grouped DataFrames
        grouped_dfs.append(loc_df)

    # Concatenate all the grouped DataFrames back together
    X_train = pd.concat(grouped_dfs)
    X_train.sort_index(inplace=True)
    print(X_train["group"].head())
```

```python
X_train.drop(columns=to_drop, inplace=True)
X_test.drop(columns=to_drop, inplace=True)

X_train.to_csv('X_train_raw.csv', index=True)
X_test.to_csv('X_test_raw.csv', index=True)
```

```
absolute_humidity_2m:gm3                 7.625
air_density_2m:kgm3                      1.2215
ceiling_height_agl:m                  3644.050049
clear_sky_energy_1h:J              2896336.75
clear_sky_rad:W                        753.849976
cloud_base_agl:m                      3644.050049
dew_or_rime:idx                          0.0
dew_point_2m:K                         280.475006
diffuse_rad:W                          127.475006
diffuse_rad_1h:J                    526032.625
direct_rad:W                           488.0
direct_rad_1h:J                    1718048.625
effective_cloud_cover:p                 18.200001
elevation:m                              6.0
fresh_snow_12h:cm                        0.0
fresh_snow_1h:cm                         0.0
fresh_snow_24h:cm                        0.0
fresh_snow_3h:cm                         0.0
fresh_snow_6h:cm                         0.0
is_day:idx                               1.0
is_in_shadow:idx                         0.0
msl_pressure:hPa                      1026.775024
precip_5min:mm                           0.0
precip_type_5min:idx                     0.0
pressure_100m:hPa                     1013.599976
pressure_50m:hPa                      1019.599976
prob_rime:p                              0.0
rain_water:kgm2                          0.0
relative_humidity_1000hPa:p             53.825001
sfc_pressure:hPa                      1025.699951
snow_density:kgm3                        NaN
snow_depth:cm                            0.0
snow_drift:idx                           0.0
snow_melt_10min:mm                       0.0
snow_water:kgm2                          0.0
sun_azimuth:d                          222.089005
sun_elevation:d                         44.503498
```

```
super_cooled_liquid_water:kgm2           0.0
t_1000hPa:K                       286.700012
total_cloud_cover:p                18.200001
visibility:m                        52329.25
wind_speed_10m:ms                        2.6
wind_speed_u_10m:ms                     -1.9
wind_speed_v_10m:ms                    -1.75
wind_speed_w_1000hPa:ms                  0.0
is_estimated                               0
y                                    4367.44
location                                   A
Name: 2019-06-11 13:00:00, dtype: object
                     absolute_humidity_2m:gm3  air_density_2m:kgm3  \
ds
2019-06-02 23:00:00                       7.7               1.2235

                     ceiling_height_agl:m  clear_sky_energy_1h:J  \
ds
2019-06-02 23:00:00           1689.824951                    0.0

                     clear_sky_rad:W  cloud_base_agl:m  dew_or_rime:idx  \
ds
2019-06-02 23:00:00              0.0       1689.824951              0.0

                     dew_point_2m:K  diffuse_rad:W  diffuse_rad_1h:J  …  \
ds                                                                    …
2019-06-02 23:00:00      280.299988            0.0               0.0  …

                     t_1000hPa:K  total_cloud_cover:p  visibility:m  \
ds
2019-06-02 23:00:00   286.899994                100.0  33770.648438

                     wind_speed_10m:ms  wind_speed_u_10m:ms  \
ds
2019-06-02 23:00:00               3.35                -3.35

                     wind_speed_v_10m:ms  wind_speed_w_1000hPa:ms  \
ds
2019-06-02 23:00:00                0.275                      0.0

                     is_estimated    y  location
ds
2019-06-02 23:00:00             0  0.0         A

[1 rows x 48 columns]
```

[55]:
```
# Create a plot of X_train showing its "y" and color it based on the value of␣
↪the sample_weight column.
if "sample_weight" in X_train.columns:
    import matplotlib.pyplot as plt
    import seaborn as sns
    sns.scatterplot(data=X_train, x=X_train.index, y="y", hue="sample_weight",␣
↪palette="deep", size=3)
    plt.show()
```

[60]:
```
def normalize_sample_weights_per_location(df):
    for loc in locations:
        loc_df = df[df["location"] == loc]
        loc_df["sample_weight"] = loc_df["sample_weight"] /␣
↪loc_df["sample_weight"].sum() * loc_df.shape[0]
        df[df["location"] == loc] = loc_df
    return df

import pandas as pd

def split_and_shuffle_data(input_data, num_bins, frac1):
    """
    Splits the input_data into num_bins and shuffles them, then divides the␣
↪bins into two datasets based on the given fraction for the first set.

    Args:
        input_data (pd.DataFrame): The data to be split and shuffled.
        num_bins (int): The number of bins to split the data into.
        frac1 (float): The fraction of each bin to go into the first output␣
↪dataset.

    Returns:
        pd.DataFrame, pd.DataFrame: The two output datasets.
    """
    # Validate the input fraction
    if frac1 < 0 or frac1 > 1:
        raise ValueError("frac1 must be between 0 and 1.")

    if frac1==1:
        return input_data, pd.DataFrame()

    # Calculate the fraction for the second output set
    frac2 = 1 - frac1


    # Shuffle the data and split into 2 based on frac1
    np.random.seed(0)
    shuffled_data = input_data.sample(frac=1)
```

```
    output_data1 = shuffled_data.iloc[:int(len(input_data) * frac1)]
    output_data2 = shuffled_data.iloc[int(len(input_data) * frac1):]

    return output_data1, output_data2


    # # Calculate bin size
    # bin_size = len(input_data) // num_bins

    # # Initialize empty DataFrames for output
    # output_data1 = pd.DataFrame()
    # output_data2 = pd.DataFrame()

    # for i in range(num_bins):
    #     # Shuffle the data in the current bin
    #     np.random.seed(i)
    #     current_bin = input_data.iloc[i * bin_size: (i + 1) * bin_size].
↪sample(frac=1)

    #     # Calculate the sizes for each output set
    #     size1 = int(len(current_bin) * frac1)

    #     # Split and append to output DataFrames
    #     output_data1 = pd.concat([output_data1, current_bin.iloc[:size1]])
    #     output_data2 = pd.concat([output_data2, current_bin.iloc[size1:]])

    # # Shuffle and split the remaining data
    # remaining_data = input_data.iloc[num_bins * bin_size:].sample(frac=1)

    # remaining_size1 = int(len(remaining_data) * frac1)

    # output_data1 = pd.concat([output_data1, remaining_data.iloc[:
↪remaining_size1]])
    # output_data2 = pd.concat([output_data2, remaining_data.
↪iloc[remaining_size1:]])

    # return output_data1, output_data2
```

[61]:
```
from autogluon.tabular import TabularDataset, TabularPredictor
data = TabularDataset('X_train_raw.csv')
# set group column of train_data be increasing from 0 to 7 based on time, the␣
↪first 1/8 of the data is group 0, the second 1/8 of the data is group 1, etc.
data['ds'] = pd.to_datetime(data['ds'])
data = data.sort_values(by='ds')

# # print size of the group for each location
# for loc in locations:
```

```
#     print(f"Location {loc}:")
#     print(train_data[train_data["location"] == loc].groupby('group').size())


# get end date of train data and subtract 3 months
#split_time = pd.to_datetime(train_data["ds"]).max() - pd.
↪Timedelta(hours=tune_and_test_length)
# 2022-10-28 22:00:00
split_time = pd.to_datetime("2022-10-28 22:00:00")
train_set = TabularDataset(data[data["ds"] < split_time])
estimated_set = TabularDataset(data[data["ds"] >= split_time]) # only estimated

test_set = pd.DataFrame()
tune_set = pd.DataFrame()
new_train_set = pd.DataFrame()

if not use_tune_data:
    raise Exception("Not implemented")

for location in locations:
    loc_data = data[data["location"] == location]
    num_train_rows = len(loc_data)

    tune_rows = 1500.0 # 2500.0
    if use_test_data:
        tune_rows = 1880.0#max(3000.0,␣
↪len(estimated_set[estimated_set["location"] == location]))

    holdout_frac = max(0.01, min(0.1, tune_rows / num_train_rows)) *␣
↪num_train_rows / len(estimated_set[estimated_set["location"] == location])

    print(f"Size of estimated for location {location}:␣
↪{len(estimated_set[estimated_set['location'] == location])}. Holdout frac␣
↪should be % of estimated: {holdout_frac}")

    # shuffle and split data
    loc_tune_set, loc_new_train_set =␣
↪split_and_shuffle_data(estimated_set[estimated_set['location'] == location],␣
↪40, holdout_frac)
    print(f"Length of location tune set : {len(loc_tune_set)}")
    new_train_set = pd.concat([new_train_set, loc_new_train_set])

    if use_test_data:
        loc_test_set, loc_tune_set = split_and_shuffle_data(loc_tune_set, 40, 0.
↪2)
        test_set = pd.concat([test_set, loc_test_set])
```

```
    tune_set = pd.concat([tune_set, loc_tune_set])



print("Length of train set before adding test set", len(train_set))
# add rest to train_set
train_set = pd.concat([train_set, new_train_set])
print("Length of train set after adding test set", len(train_set))




if use_groups:
    test_set = test_set.drop(columns=['group'])


tuning_data = tune_set

# number of rows in tuning data for each location
print("Shapes of tuning data", tuning_data.groupby('location').size())



if use_test_data:
    test_data = test_set
    print("Shape of test", test_data.shape[0])


train_data = train_set

# ensure sample weights for your training (or tuning) data sum to the number of␣
↪rows in the training (or tuning) data.
if weight_evaluation:
    # ensure sample weights for data sum to the number of rows in the tuning /
↪train data.
    tuning_data = normalize_sample_weights_per_location(tuning_data)
    train_data = normalize_sample_weights_per_location(train_data)
    if use_test_data:
        test_data = normalize_sample_weights_per_location(test_data)


train_data = TabularDataset(train_data)
tuning_data = TabularDataset(tuning_data)

if use_test_data:
```

```
    test_data = TabularDataset(test_data)
```

```
Size of estimated for location A: 4214. Holdout frac should be % of estimated:
0.4461319411485524
Length of location tune set : 1880
Size of estimated for location B: 3533. Holdout frac should be % of estimated:
0.5321256722332296
Length of location tune set : 1880
Size of estimated for location C: 2923. Holdout frac should be % of estimated:
0.6431748203900103
Length of location tune set : 1880
Length of train set before adding test set 77247
Length of train set after adding test set 82277
Shapes of tuning data location
A    1504
B    1504
C    1504
dtype: int64
Shape of test 1128
```

## 3 Quick EDA

[62]:
```
if run_analysis:
    import autogluon.eda.auto as auto
    auto.dataset_overview(train_data=train_data, test_data=test_data,␣
 ↪label="y", sample=None)
```

[63]:
```
if run_analysis:
    auto.target_analysis(train_data=train_data, label="y", sample=None)
```

## 4 Modeling

[64]:
```
import os



# Get the last submission number
last_submission_number = int(max([int(filename.split('_')[1].split('.')[0]) for␣
 ↪filename in os.listdir('submissions') if "submission" in filename]))
print("Last submission number:", last_submission_number)
print("Now creating submission number:", last_submission_number + 1)

# Create the new filename
new_filename = f'submission_{last_submission_number + 1}'

hello = os.environ.get('HELLO')
if hello is not None:
```

```
    new_filename += f'_{hello}'

print("New filename:", new_filename)
```

```
Last submission number: 122
Now creating submission number: 123
New filename: submission_123_jorge
```

[65]:
```
predictors = [None, None, None]
```

[66]:
```
def fit_predictor_for_location(loc):
    print(f"Training model for location {loc}...")
    # sum of sample weights for this location, and number of rows, for both␣
↪train and tune data and test data
    if weight_evaluation:
        print("Train data sample weight sum:",␣
↪train_data[train_data["location"] == loc]["sample_weight"].sum())
        print("Train data number of rows:", train_data[train_data["location"]␣
↪== loc].shape[0])
        if use_tune_data:
            print("Tune data sample weight sum:",␣
↪tuning_data[tuning_data["location"] == loc]["sample_weight"].sum())
            print("Tune data number of rows:",␣
↪tuning_data[tuning_data["location"] == loc].shape[0])
        if use_test_data:
            print("Test data sample weight sum:",␣
↪test_data[test_data["location"] == loc]["sample_weight"].sum())
            print("Test data number of rows:", test_data[test_data["location"]␣
↪== loc].shape[0])
    predictor = TabularPredictor(
        label=label,
        eval_metric=metric,
        path=f"AutogluonModels/{new_filename}_{loc}",
        # sample_weight=sample_weight,
        # weight_evaluation=weight_evaluation,
        # groups="group" if use_groups else None,
    ).fit(
        train_data=train_data[train_data["location"] == loc].
↪drop(columns=["ds"]),
        time_limit=time_limit,
        presets=presets,
        num_stack_levels=num_stack_levels,
        num_bag_folds=num_bag_folds if not use_groups else 2,# just put␣
↪somethin, will be overwritten anyways
        num_bag_sets=num_bag_sets,
        tuning_data=tuning_data[tuning_data["location"] == loc].
↪reset_index(drop=True).drop(columns=["ds"]) if use_tune_data else None,
```

```
        use_bag_holdout=use_bag_holdout,
        # holdout_frac=holdout_frac,
        excluded_model_types=excluded_model_types
    )

    # evaluate on test data
    if use_test_data:
        # drop sample_weight column
        t = test_data[test_data["location"] == loc]#.
↪drop(columns=["sample_weight"])
        perf = predictor.evaluate(t)
        print("Evaluation on test data:")
        print(perf[predictor.eval_metric.name])

    return predictor

loc = "A"
predictors[0] = fit_predictor_for_location(loc)
```

```
Warning: path already exists! This predictor may overwrite an existing
predictor! path="AutogluonModels/submission_123_jorge_A"
Presets specified: ['best_quality']
Stack configuration (auto_stack=True): num_stack_levels=0, num_bag_folds=8,
num_bag_sets=20
Beginning AutoGluon training … Time limit = 600s
AutoGluon will save models to "AutogluonModels/submission_123_jorge_A/"
AutoGluon Version:  0.8.1
Python Version:     3.10.12
Operating System:   Darwin
Platform Machine:   arm64
Platform Version:   Darwin Kernel Version 22.1.0: Sun Oct  9 20:15:09 PDT 2022;
root:xnu-8792.41.9~2/RELEASE_ARM64_T6000
Disk Space Avail:   131.19 GB / 494.38 GB (26.5%)
Train Data Rows:    30900
Train Data Columns: 44
Tuning Data Rows:    1504
Tuning Data Columns: 44
Label Column: y
Preprocessing data …
AutoGluon infers your prediction problem is: 'regression' (because dtype of
label-column == float and many unique label-values observed).
        Label info (max, min, mean, stddev): (5733.42, 0.0, 674.06946,
1195.52285)
        If 'regression' is not the correct problem_type, please manually specify
the problem_type parameter during predictor init (You may specify problem_type
as one of: ['binary', 'multiclass', 'regression'])
Using Feature Generators to preprocess the data …
Fitting AutoMLPipelineFeatureGenerator…
```

```
        Available Memory:                    3016.0 MB
        Train Data (Original)  Memory Usage: 13.03 MB (0.4% of available memory)
        Inferring data type of each feature based on column values. Set
feature_metadata_in to manually specify special dtypes of the features.
        Stage 1 Generators:
                Fitting AsTypeFeatureGenerator…
                        Note: Converting 2 features to boolean dtype as they
only contain 2 unique values.
        Stage 2 Generators:
                Fitting FillNaFeatureGenerator…
        Stage 3 Generators:
                Fitting IdentityFeatureGenerator…
        Stage 4 Generators:
                Fitting DropUniqueFeatureGenerator…
        Stage 5 Generators:
                Fitting DropDuplicatesFeatureGenerator…
        Useless Original Features (Count: 3): ['elevation:m', 'snow_drift:idx',
'location']
                These features carry no predictive signal and should be manually
investigated.

Training model for location A…

                This is typically a feature which has the same value for all
rows.
                These features do not need to be present at inference time.
        Types of features in original data (raw dtype, special dtypes):
                ('float', []) : 40 | ['absolute_humidity_2m:gm3',
'air_density_2m:kgm3', 'ceiling_height_agl:m', 'clear_sky_energy_1h:J',
'clear_sky_rad:W', …]
                ('int', [])   :  1 | ['is_estimated']
        Types of features in processed data (raw dtype, special dtypes):
                ('float', [])     : 39 | ['absolute_humidity_2m:gm3',
'air_density_2m:kgm3', 'ceiling_height_agl:m', 'clear_sky_energy_1h:J',
'clear_sky_rad:W', …]
                ('int', ['bool']) :  2 | ['snow_density:kgm3', 'is_estimated']
        0.1s = Fit runtime
        41 features in original data used to generate 41 features in processed
data.
        Train Data (Processed) Memory Usage: 10.17 MB (0.3% of available memory)
Data preprocessing and feature engineering runtime = 0.13s …
AutoGluon will gauge predictive performance using evaluation metric:
'mean_absolute_error'
        This metric's sign has been flipped to adhere to being higher_is_better.
The metric score can be multiplied by -1 to get the metric value.
        To change this, specify the eval_metric parameter of Predictor()
use_bag_holdout=True, will use tuning_data as holdout (will not be used for
early stopping).
User-specified model hyperparameters to be fit:
```

```
{
        'NN_TORCH': {},
        'GBM': [{'extra_trees': True, 'ag_args': {'name_suffix': 'XT'}}, {},
'GBMLarge'],
        'CAT': {},
        'XGB': {},
        'FASTAI': {},
        'RF': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'XT': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'KNN': [{'weights': 'uniform', 'ag_args': {'name_suffix': 'Unif'}},
{'weights': 'distance', 'ag_args': {'name_suffix': 'Dist'}}],
}
Excluded models: ['CAT', 'XGB', 'RF'] (Specified by `excluded_model_types`)
Fitting 8 L1 models …
Fitting model: KNeighborsUnif_BAG_L1 … Training model for up to 599.87s of the
599.86s of remaining time.
        -190.3604        = Validation score   (-mean_absolute_error)
        0.02s    = Training   runtime
        119.71s  = Validation runtime
Fitting model: KNeighborsDist_BAG_L1 … Training model for up to 469.32s of the
469.32s of remaining time.
        -191.9073        = Validation score   (-mean_absolute_error)
        0.02s    = Training   runtime
        144.07s  = Validation runtime
Fitting model: LightGBMXT_BAG_L1 … Training model for up to 313.98s of the
313.97s of remaining time.
Will use sequential fold fitting strategy because import of ray failed. Reason:
ray is required to train folds in parallel. A quick tip is to install via `pip
install ray==2.2.0`, or use sequential fold fitting by passing
`sequential_local` to `ag_args_ensemble` when calling tabular.fitFor example:
`predictor.fit(…, ag_args_ensemble={'fold_fitting_strategy':
'sequential_local'})`
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
SequentialLocalFoldFittingStrategy

[1000]  valid_set's l1: 185.053
[2000]  valid_set's l1: 178.583
[3000]  valid_set's l1: 175.707
[4000]  valid_set's l1: 173.75
[5000]  valid_set's l1: 172.185
```

```
[6000]  valid_set's l1: 171.275
[7000]  valid_set's l1: 170.604
        Ran out of time, early stopping on iteration 7828. Best iteration is:
        [7827]  valid_set's l1: 170.153
[1000]  valid_set's l1: 193.64
[2000]  valid_set's l1: 188.558
[3000]  valid_set's l1: 185.938
        Ran out of time, early stopping on iteration 3715. Best iteration is:
        [3641]  valid_set's l1: 184.827
[1000]  valid_set's l1: 180.83
[2000]  valid_set's l1: 175.11
[3000]  valid_set's l1: 171.77
[4000]  valid_set's l1: 170.097
[5000]  valid_set's l1: 169.015
[6000]  valid_set's l1: 168.407
[7000]  valid_set's l1: 168.011
[8000]  valid_set's l1: 167.395
        Ran out of time, early stopping on iteration 8115. Best iteration is:
        [8025]  valid_set's l1: 167.363
[1000]  valid_set's l1: 188.99
[2000]  valid_set's l1: 183.143
[3000]  valid_set's l1: 179.848
[4000]  valid_set's l1: 178.118
        Ran out of time, early stopping on iteration 4643. Best iteration is:
        [4631]  valid_set's l1: 177.531
[1000]  valid_set's l1: 180.043
[2000]  valid_set's l1: 174.672
[3000]  valid_set's l1: 172.512
[4000]  valid_set's l1: 170.112
        Ran out of time, early stopping on iteration 4839. Best iteration is:
        [4834]  valid_set's l1: 168.704
[1000]  valid_set's l1: 173.671
[2000]  valid_set's l1: 169.207
[3000]  valid_set's l1: 167.027
        Ran out of time, early stopping on iteration 3760. Best iteration is:
        [3666]  valid_set's l1: 166.002
[1000]  valid_set's l1: 189.372
[2000]  valid_set's l1: 184.316
[3000]  valid_set's l1: 182.143
[4000]  valid_set's l1: 180.329
[5000]  valid_set's l1: 179.437
[6000]  valid_set's l1: 178.553
```

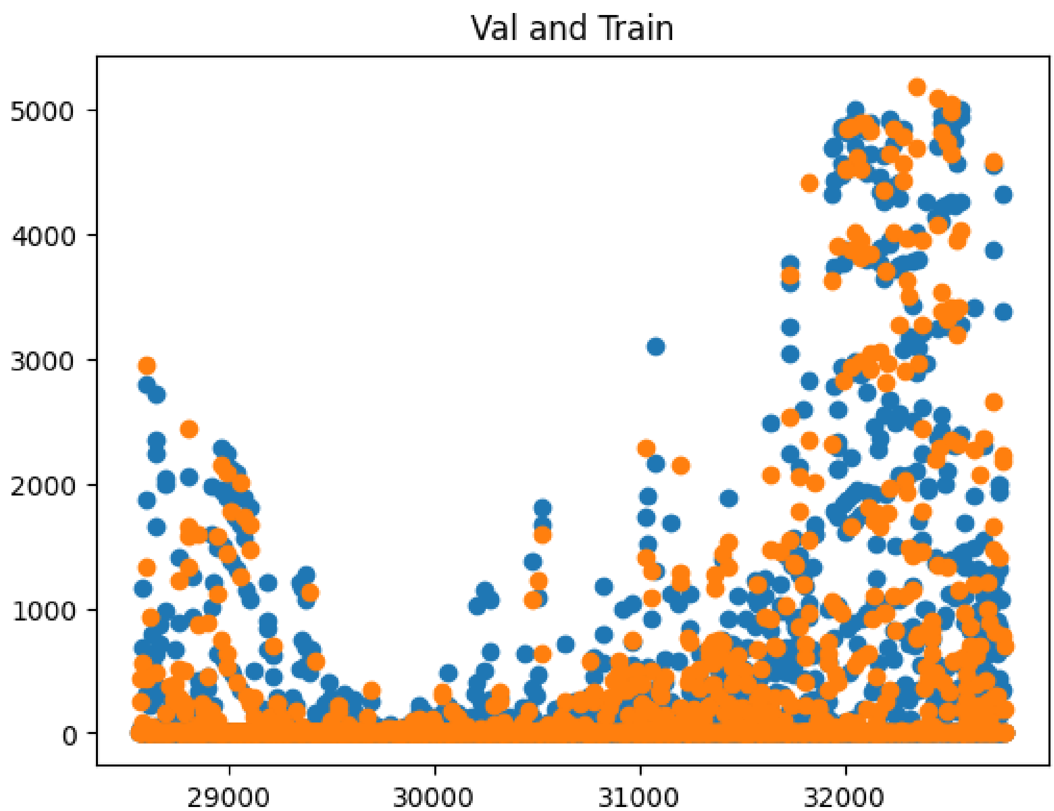
```
[7000]  valid_set's l1: 178.221
[8000]  valid_set's l1: 177.73
        Ran out of time, early stopping on iteration 8677. Best iteration is:
        [8656]  valid_set's l1: 177.451
[1000]  valid_set's l1: 182.091
[2000]  valid_set's l1: 176.068
[3000]  valid_set's l1: 172.904
[4000]  valid_set's l1: 170.874
[5000]  valid_set's l1: 169.534
[6000]  valid_set's l1: 168.54
[7000]  valid_set's l1: 167.609
[8000]  valid_set's l1: 167.049
        Ran out of time, early stopping on iteration 8332. Best iteration is:
        [8332]  valid_set's l1: 166.879
        -81.5193         = Validation score   (-mean_absolute_error)
        298.32s  = Training   runtime
        2.78s    = Validation runtime
Fitting model: LightGBM_BAG_L1 … Training model for up to 9.09s of the 9.09s
of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
SequentialLocalFoldFittingStrategy
        Ran out of time, early stopping on iteration 34. Best iteration is:
        [34]    valid_set's l1: 296.732
        Ran out of time, early stopping on iteration 41. Best iteration is:
        [41]    valid_set's l1: 273.849
        Ran out of time, early stopping on iteration 48. Best iteration is:
        [48]    valid_set's l1: 245.869
        Ran out of time, early stopping on iteration 40. Best iteration is:
        [40]    valid_set's l1: 281.07
        Ran out of time, early stopping on iteration 41. Best iteration is:
        [41]    valid_set's l1: 263.936
        Ran out of time, early stopping on iteration 45. Best iteration is:
        [45]    valid_set's l1: 248.645
        Ran out of time, early stopping on iteration 54. Best iteration is:
        [54]    valid_set's l1: 241.851
        Ran out of time, early stopping on iteration 77. Best iteration is:
        [77]    valid_set's l1: 210.857
        -176.5173        = Validation score   (-mean_absolute_error)
        8.72s    = Training   runtime
        0.03s    = Validation runtime
Fitting model: ExtraTreesMSE_BAG_L1 … Training model for up to 0.27s of the
0.27s of remaining time.
        -102.3261        = Validation score   (-mean_absolute_error)
        3.52s    = Training   runtime
        0.59s    = Validation runtime
Completed 1/20 k-fold bagging repeats …
```

```
Fitting model: WeightedEnsemble_L2 … Training model for up to 360.0s of the
-4.4s of remaining time.
        -81.5193         = Validation score   (-mean_absolute_error)
        0.05s    = Training   runtime
        0.0s     = Validation runtime
AutoGluon training complete, total runtime = 604.47s … Best model:
"WeightedEnsemble_L2"
TabularPredictor saved. To load, use: predictor =
TabularPredictor.load("AutogluonModels/submission_123_jorge_A/")
Evaluation: mean_absolute_error on test data: -90.96713168170461
        Note: Scores are always higher_is_better. This metric score can be
multiplied by -1 to get the metric value.
Evaluations on test data:
{
    "mean_absolute_error": -90.96713168170461,
    "root_mean_squared_error": -243.00511998167275,
    "mean_squared_error": -59051.488337307164,
    "r2": 0.9243448828490051,
    "pearsonr": 0.961569748463051,
    "median_absolute_error": -5.074539422988892
}

Evaluation on test data:
-90.96713168170461
```

[67]:

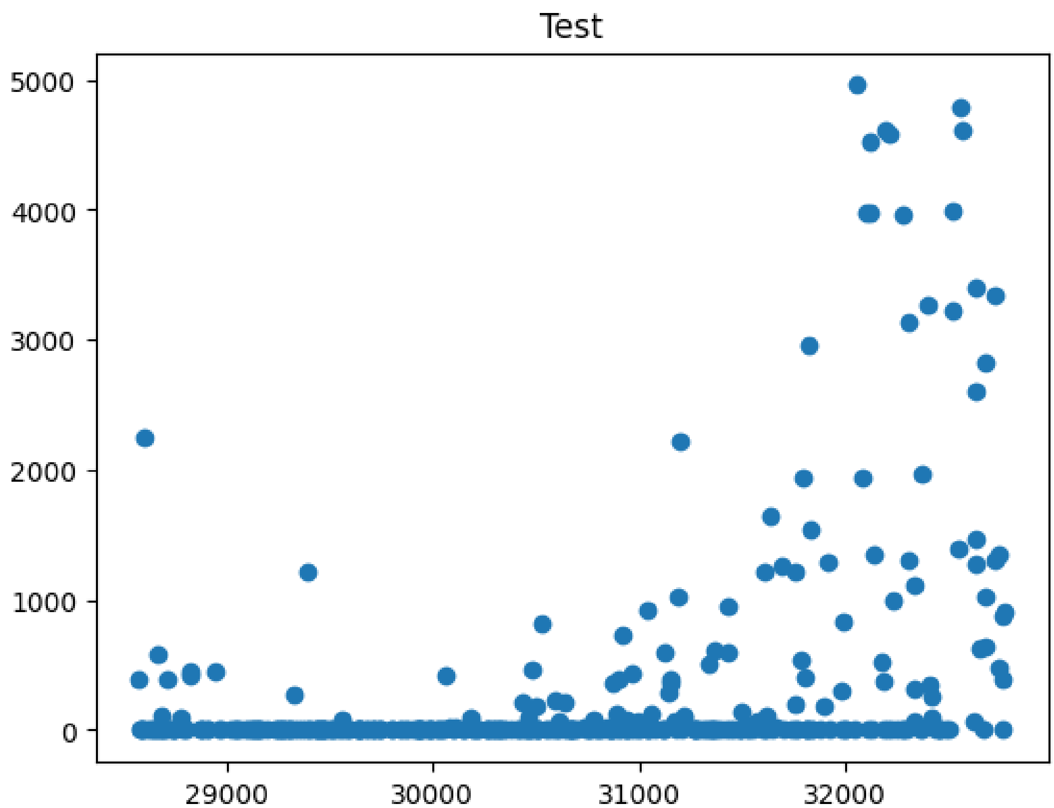
```python
import matplotlib.pyplot as plt
leaderboards = [None, None, None]
def leaderboard_for_location(i, loc):
    if use_tune_data:
        plt.scatter(train_data[(train_data["location"] == loc) &␣
↪(train_data["is_estimated"]==True)]["y"].index,␣
↪train_data[(train_data["location"] == loc) &␣
↪(train_data["is_estimated"]==True)]["y"])
        plt.scatter(tuning_data[tuning_data["location"] == loc]["y"].index,␣
↪tuning_data[tuning_data["location"] == loc]["y"])
        plt.title("Val and Train")
        plt.show()

        if use_test_data:
            lb = predictors[i].leaderboard(test_data[test_data["location"] ==␣
↪loc])
            lb["location"] = loc
            plt.scatter(test_data[test_data["location"] == loc]["y"].index,␣
↪test_data[test_data["location"] == loc]["y"])
            plt.title("Test")

            return lb
```

```
    return pd.DataFrame()

leaderboards[0] = leaderboard_for_location(0, loc)
```




```
                  model  score_test   score_val  pred_time_test  pred_time_val
fit_time  pred_time_test_marginal  pred_time_val_marginal  fit_time_marginal
stack_level  can_infer  fit_order
0       LightGBMXT_BAG_L1  -90.967132  -81.519269        0.610966       2.777259
298.320478                0.610966                2.777259         298.320478
1        True          3
1     WeightedEnsemble_L2  -90.967132  -81.519269        0.612448       2.777490
298.370370                0.001482                0.000231           0.049892
2        True          6
2    ExtraTreesMSE_BAG_L1 -103.476840 -102.326132        0.237853       0.588659
3.523309                0.237853                0.588659           3.523309
1        True          5
3          LightGBM_BAG_L1 -165.818687 -176.517330        0.017727       0.030071
8.717963                0.017727                0.030071           8.717963
1        True          4
4  KNeighborsUnif_BAG_L1 -170.349627 -190.360353        2.763736     119.714988
0.022840                2.763736              119.714988           0.022840
```

```
1       True           1
5  KNeighborsDist_BAG_L1 -176.177754 -191.907283        2.139242      144.067278
0.022986                 2.139242              144.067278           0.022986
1       True           2
```




[68]:
```python
loc = "B"
predictors[1] = fit_predictor_for_location(loc)
leaderboards[1] = leaderboard_for_location(1, loc)
```

```
Presets specified: ['best_quality']
Stack configuration (auto_stack=True): num_stack_levels=0, num_bag_folds=8,
num_bag_sets=20
Beginning AutoGluon training … Time limit = 600s
AutoGluon will save models to "AutogluonModels/submission_123_jorge_B/"
AutoGluon Version:  0.8.1
Python Version:     3.10.12
Operating System:   Darwin
Platform Machine:   arm64
Platform Version:   Darwin Kernel Version 22.1.0: Sun Oct  9 20:15:09 PDT 2022;
root:xnu-8792.41.9~2/RELEASE_ARM64_T6000
Disk Space Avail:   130.64 GB / 494.38 GB (26.4%)
Train Data Rows:    27343
```

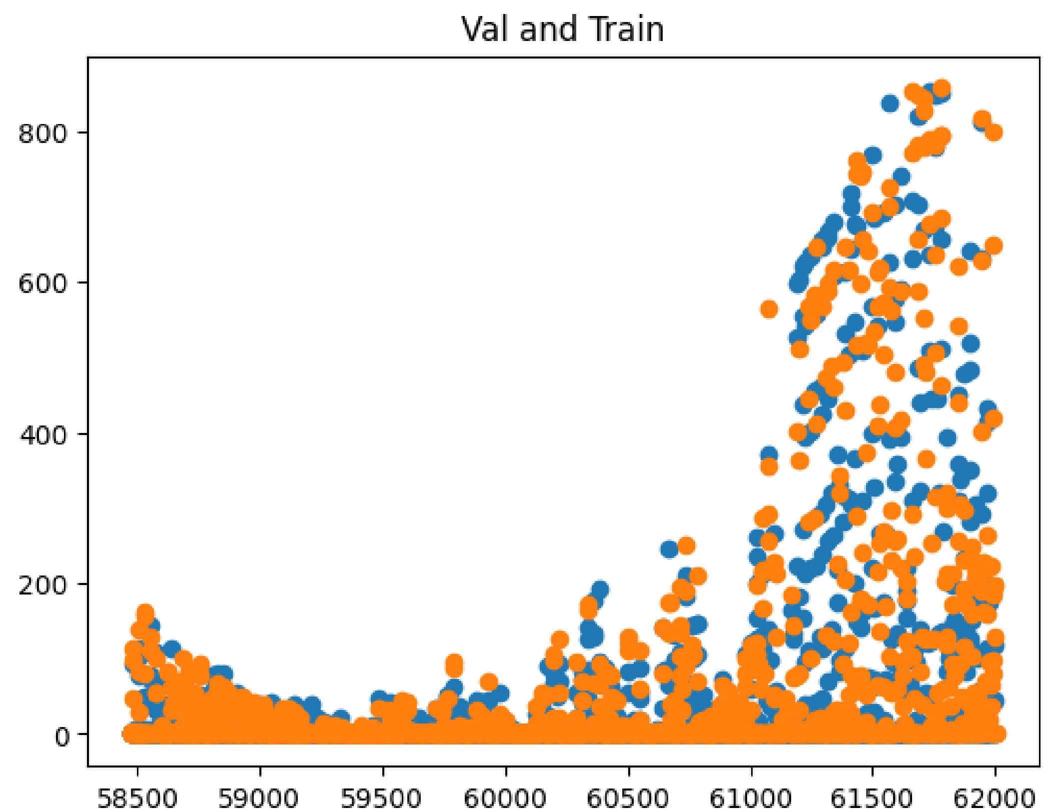
```
Train Data Columns: 44
Tuning Data Rows:    1504
Tuning Data Columns: 44
Label Column: y
Preprocessing data …
AutoGluon infers your prediction problem is: 'regression' (because dtype of
label-column == float and many unique label-values observed).
        Label info (max, min, mean, stddev): (1152.3, -0.0, 97.86121, 206.22589)
        If 'regression' is not the correct problem_type, please manually specify
the problem_type parameter during predictor init (You may specify problem_type
as one of: ['binary', 'multiclass', 'regression'])
Using Feature Generators to preprocess the data …
Fitting AutoMLPipelineFeatureGenerator…
        Available Memory:                    2833.33 MB
        Train Data (Original)  Memory Usage: 11.6 MB (0.4% of available memory)
        Inferring data type of each feature based on column values. Set
feature_metadata_in to manually specify special dtypes of the features.
        Stage 1 Generators:
                Fitting AsTypeFeatureGenerator…
                        Note: Converting 2 features to boolean dtype as they
only contain 2 unique values.
        Stage 2 Generators:
                Fitting FillNaFeatureGenerator…
        Stage 3 Generators:
                Fitting IdentityFeatureGenerator…
        Stage 4 Generators:
                Fitting DropUniqueFeatureGenerator…
        Stage 5 Generators:
                Fitting DropDuplicatesFeatureGenerator…
        Useless Original Features (Count: 2): ['elevation:m', 'location']
                These features carry no predictive signal and should be manually
investigated.
                This is typically a feature which has the same value for all
rows.
                These features do not need to be present at inference time.
        Types of features in original data (raw dtype, special dtypes):
                ('float', []) : 41 | ['absolute_humidity_2m:gm3',
'air_density_2m:kgm3', 'ceiling_height_agl:m', 'clear_sky_energy_1h:J',
'clear_sky_rad:W', …]
                ('int', [])   :  1 | ['is_estimated']
        Types of features in processed data (raw dtype, special dtypes):
                ('float', [])     : 40 | ['absolute_humidity_2m:gm3',
'air_density_2m:kgm3', 'ceiling_height_agl:m', 'clear_sky_energy_1h:J',
'clear_sky_rad:W', …]
                ('int', ['bool']) :  2 | ['snow_density:kgm3', 'is_estimated']
        0.1s = Fit runtime
        42 features in original data used to generate 42 features in processed
data.
```

```
        Train Data (Processed) Memory Usage: 9.29 MB (0.3% of available memory)
Data preprocessing and feature engineering runtime = 0.11s …

Training model for location B…

AutoGluon will gauge predictive performance using evaluation metric:
'mean_absolute_error'
        This metric's sign has been flipped to adhere to being higher_is_better.
The metric score can be multiplied by -1 to get the metric value.
        To change this, specify the eval_metric parameter of Predictor()
use_bag_holdout=True, will use tuning_data as holdout (will not be used for
early stopping).
User-specified model hyperparameters to be fit:
{
        'NN_TORCH': {},
        'GBM': [{'extra_trees': True, 'ag_args': {'name_suffix': 'XT'}}, {},
'GBMLarge'],
        'CAT': {},
        'XGB': {},
        'FASTAI': {},
        'RF': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'XT': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'KNN': [{'weights': 'uniform', 'ag_args': {'name_suffix': 'Unif'}},
{'weights': 'distance', 'ag_args': {'name_suffix': 'Dist'}}],
}
Excluded models: ['CAT', 'XGB', 'RF'] (Specified by `excluded_model_types`)
Fitting 8 L1 models …
Fitting model: KNeighborsUnif_BAG_L1 … Training model for up to 599.89s of the
599.89s of remaining time.
        -31.0941         = Validation score   (-mean_absolute_error)
        0.02s    = Training   runtime
        112.29s  = Validation runtime
Fitting model: KNeighborsDist_BAG_L1 … Training model for up to 479.9s of the
479.9s of remaining time.
        -30.6152         = Validation score   (-mean_absolute_error)
        0.04s    = Training   runtime
        117.99s  = Validation runtime
Fitting model: LightGBMXT_BAG_L1 … Training model for up to 353.48s of the
353.48s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
SequentialLocalFoldFittingStrategy
```

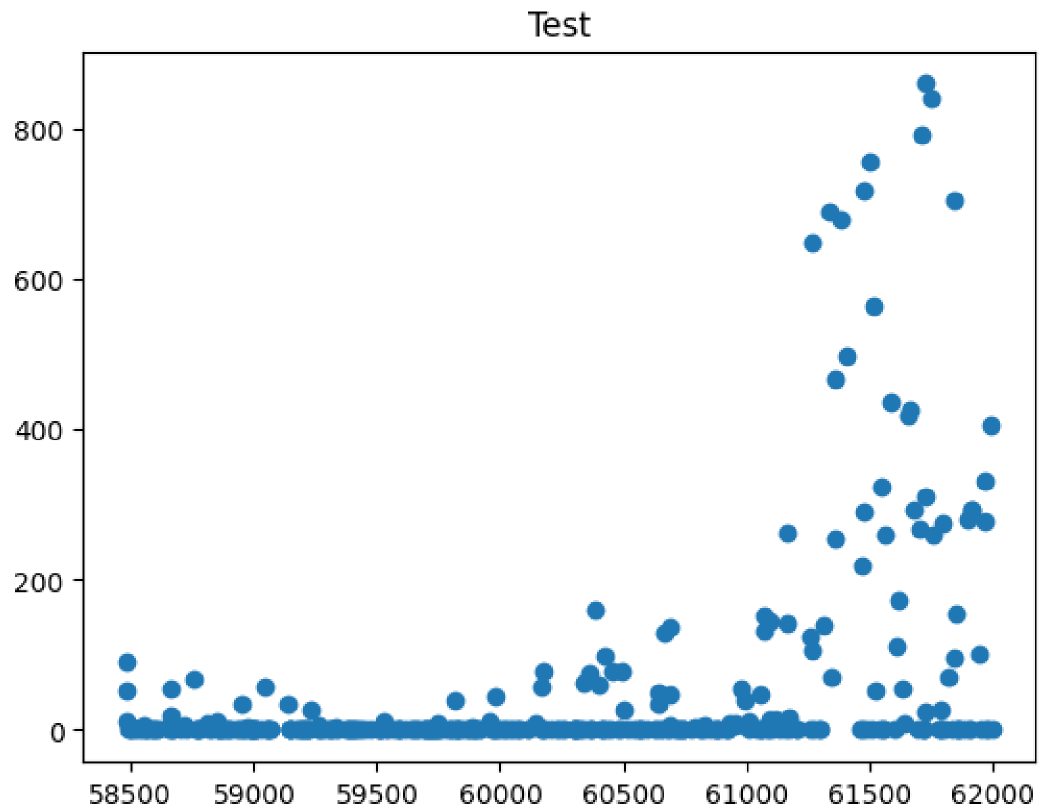
```
[1000]  valid_set's l1: 23.7938
[2000]  valid_set's l1: 22.8059
[3000]  valid_set's l1: 22.3022
[4000]  valid_set's l1: 21.9856
[5000]  valid_set's l1: 21.7541
[6000]  valid_set's l1: 21.6093
[7000]  valid_set's l1: 21.5328

        Ran out of time, early stopping on iteration 7432. Best iteration is:
        [7431]  valid_set's l1: 21.4881

[1000]  valid_set's l1: 25.6285
[2000]  valid_set's l1: 24.3508
[3000]  valid_set's l1: 23.7804
[4000]  valid_set's l1: 23.4012
[5000]  valid_set's l1: 23.2099
[6000]  valid_set's l1: 23.0396

        Ran out of time, early stopping on iteration 6588. Best iteration is:
        [6587]  valid_set's l1: 22.9706

[1000]  valid_set's l1: 26.7749
[2000]  valid_set's l1: 25.8799
[3000]  valid_set's l1: 25.4253

        Ran out of time, early stopping on iteration 3872. Best iteration is:
        [3838]  valid_set's l1: 25.2578

[1000]  valid_set's l1: 25.4797
[2000]  valid_set's l1: 24.4554
[3000]  valid_set's l1: 24.0402
[4000]  valid_set's l1: 23.85
[5000]  valid_set's l1: 23.6779
[6000]  valid_set's l1: 23.5788

        Ran out of time, early stopping on iteration 6254. Best iteration is:
        [6241]  valid_set's l1: 23.5364

[1000]  valid_set's l1: 24.2649
[2000]  valid_set's l1: 23.4077

        Ran out of time, early stopping on iteration 2922. Best iteration is:
        [2920]  valid_set's l1: 23.0069

[1000]  valid_set's l1: 26.1133
[2000]  valid_set's l1: 25.3134
[3000]  valid_set's l1: 24.852
[4000]  valid_set's l1: 24.5618
[5000]  valid_set's l1: 24.4208

        Ran out of time, early stopping on iteration 5783. Best iteration is:
        [5757]  valid_set's l1: 24.3455
```

```
[1000]  valid_set's l1: 24.689
[2000]  valid_set's l1: 23.8422
[3000]  valid_set's l1: 23.548
        Ran out of time, early stopping on iteration 3730. Best iteration is:
        [3730]  valid_set's l1: 23.3606
[1000]  valid_set's l1: 25.663
[2000]  valid_set's l1: 24.4793
[3000]  valid_set's l1: 23.8906
[4000]  valid_set's l1: 23.5761
[5000]  valid_set's l1: 23.2969
[6000]  valid_set's l1: 23.129
[7000]  valid_set's l1: 22.9944
[8000]  valid_set's l1: 22.8871
[9000]  valid_set's l1: 22.8148
        Ran out of time, early stopping on iteration 9319. Best iteration is:
        [9319]  valid_set's l1: 22.7999
        -14.2659         = Validation score   (-mean_absolute_error)
        336.66s  = Training   runtime
        2.29s    = Validation runtime
Fitting model: LightGBM_BAG_L1 … Training model for up to 11.37s of the 11.37s
of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
SequentialLocalFoldFittingStrategy
        Ran out of time, early stopping on iteration 84. Best iteration is:
        [84]    valid_set's l1: 27.6254
        Ran out of time, early stopping on iteration 72. Best iteration is:
        [72]    valid_set's l1: 32.1105
        Ran out of time, early stopping on iteration 63. Best iteration is:
        [63]    valid_set's l1: 33.7638
        Ran out of time, early stopping on iteration 72. Best iteration is:
        [72]    valid_set's l1: 31.0883
        Ran out of time, early stopping on iteration 61. Best iteration is:
        [61]    valid_set's l1: 31.6379
        Ran out of time, early stopping on iteration 59. Best iteration is:
        [59]    valid_set's l1: 33.0372
        Ran out of time, early stopping on iteration 54. Best iteration is:
        [54]    valid_set's l1: 34.1837
        Ran out of time, early stopping on iteration 90. Best iteration is:
        [90]    valid_set's l1: 30.0823
        -22.1354         = Validation score   (-mean_absolute_error)
        10.87s   = Training   runtime
        0.03s    = Validation runtime
Fitting model: ExtraTreesMSE_BAG_L1 … Training model for up to 0.37s of the
0.36s of remaining time.
        -16.7662         = Validation score   (-mean_absolute_error)
        3.1s     = Training   runtime
```

```
        0.52s    = Validation runtime
Completed 1/20 k-fold bagging repeats …
Fitting model: WeightedEnsemble_L2 … Training model for up to 360.0s of the
-3.73s of remaining time.
        -14.197  = Validation score   (-mean_absolute_error)
        0.05s    = Training   runtime
        0.0s     = Validation runtime
AutoGluon training complete, total runtime = 603.8s … Best model:
"WeightedEnsemble_L2"
TabularPredictor saved. To load, use: predictor =
TabularPredictor.load("AutogluonModels/submission_123_jorge_B/")
Evaluation: mean_absolute_error on test data: -15.438844884969932
        Note: Scores are always higher_is_better. This metric score can be
multiplied by -1 to get the metric value.
Evaluations on test data:
{
    "mean_absolute_error": -15.438844884969932,
    "root_mean_squared_error": -46.31067375306325,
    "mean_squared_error": -2144.678503462661,
    "r2": 0.8891341296924462,
    "pearsonr": 0.9429818273324595,
    "median_absolute_error": -0.5003813803195953
}

Evaluation on test data:
-15.438844884969932
```




```
                      model  score_test  score_val  pred_time_test  pred_time_val
fit_time  pred_time_test_marginal  pred_time_val_marginal  fit_time_marginal
stack_level  can_infer  fit_order
0     WeightedEnsemble_L2  -15.438845 -14.197004        0.885067       2.806877
339.806925                 0.001305                0.000248           0.052879
2       True          6
1       LightGBMXT_BAG_L1  -15.720706 -14.265876        0.690143       2.286147
336.657248                 0.690143                2.286147         336.657248
1       True          3
2    ExtraTreesMSE_BAG_L1  -16.288915 -16.766233        0.193619       0.520482
3.096798                 0.193619                0.520482           3.096798
1       True          5
3         LightGBM_BAG_L1  -20.064119 -22.135438        0.018310       0.034770
10.872451                 0.018310                0.034770          10.872451
1       True          4
4  KNeighborsUnif_BAG_L1  -26.923013 -31.094123        1.672986     112.287918
0.017300                 1.672986              112.287918           0.017300
1       True          1
5  KNeighborsDist_BAG_L1  -27.258140 -30.615185        2.378423     117.987351
0.041716                 2.378423              117.987351           0.041716
1       True          2
```




[69]:
```
loc = "C"
predictors[2] = fit_predictor_for_location(loc)
leaderboards[2] = leaderboard_for_location(2, loc)
```

```
Presets specified: ['best_quality']
Stack configuration (auto_stack=True): num_stack_levels=0, num_bag_folds=8,
num_bag_sets=20
Beginning AutoGluon training … Time limit = 600s
AutoGluon will save models to "AutogluonModels/submission_123_jorge_C/"
AutoGluon Version:  0.8.1
Python Version:     3.10.12
Operating System:   Darwin
Platform Machine:   arm64
Platform Version:   Darwin Kernel Version 22.1.0: Sun Oct  9 20:15:09 PDT 2022;
root:xnu-8792.41.9~2/RELEASE_ARM64_T6000
Disk Space Avail:   130.22 GB / 494.38 GB (26.3%)
Train Data Rows:    24034
Train Data Columns: 44
Tuning Data Rows:    1504
Tuning Data Columns: 44
Label Column: y
```

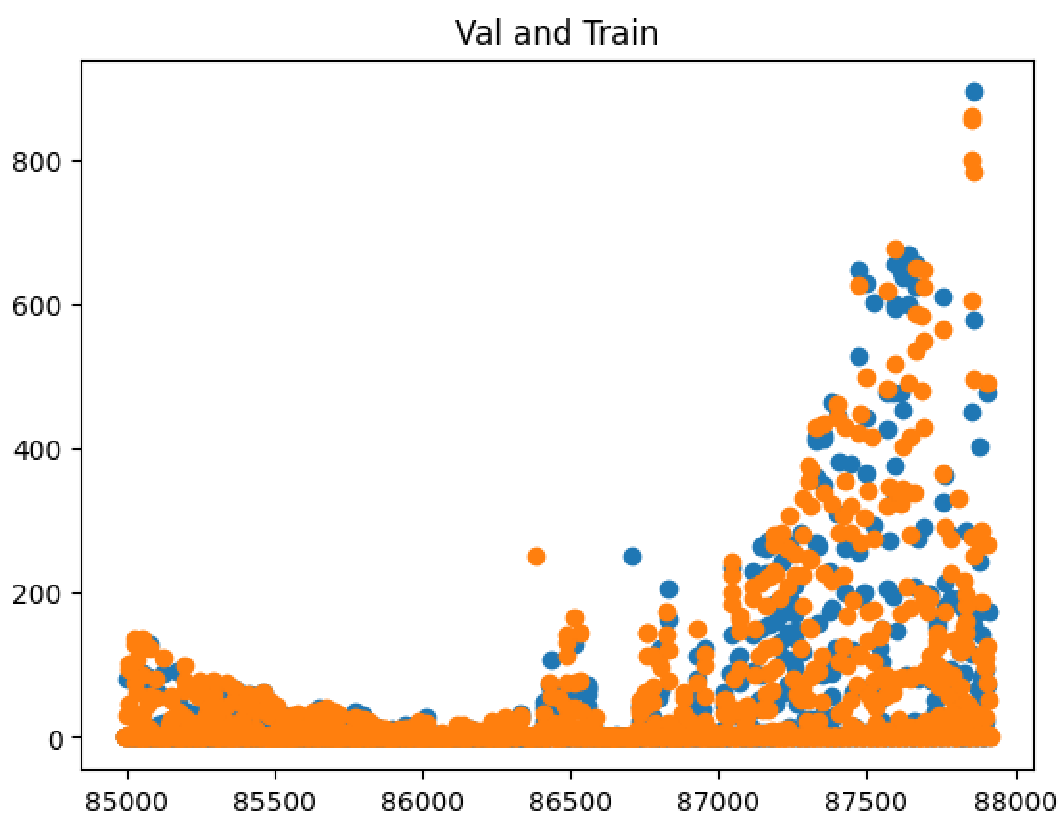
```
Preprocessing data …
AutoGluon infers your prediction problem is: 'regression' (because dtype of
label-column == float and label-values can't be converted to int).
        Label info (max, min, mean, stddev): (999.6, -0.0, 81.13701, 169.91738)
        If 'regression' is not the correct problem_type, please manually specify
the problem_type parameter during predictor init (You may specify problem_type
as one of: ['binary', 'multiclass', 'regression'])
Using Feature Generators to preprocess the data …
Fitting AutoMLPipelineFeatureGenerator…
        Available Memory:                    2783.57 MB
        Train Data (Original)  Memory Usage: 10.27 MB (0.4% of available memory)
        Inferring data type of each feature based on column values. Set
feature_metadata_in to manually specify special dtypes of the features.

Training model for location C…

        Stage 1 Generators:
                Fitting AsTypeFeatureGenerator…
                        Note: Converting 2 features to boolean dtype as they
only contain 2 unique values.
        Stage 2 Generators:
                Fitting FillNaFeatureGenerator…
        Stage 3 Generators:
                Fitting IdentityFeatureGenerator…
        Stage 4 Generators:
                Fitting DropUniqueFeatureGenerator…
        Stage 5 Generators:
                Fitting DropDuplicatesFeatureGenerator…
        Useless Original Features (Count: 3): ['elevation:m', 'snow_drift:idx',
'location']
                These features carry no predictive signal and should be manually
investigated.
                This is typically a feature which has the same value for all
rows.
                These features do not need to be present at inference time.
        Types of features in original data (raw dtype, special dtypes):
                ('float', []) : 40 | ['absolute_humidity_2m:gm3',
'air_density_2m:kgm3', 'ceiling_height_agl:m', 'clear_sky_energy_1h:J',
'clear_sky_rad:W', …]
                ('int', [])   :  1 | ['is_estimated']
        Types of features in processed data (raw dtype, special dtypes):
                ('float', [])     : 39 | ['absolute_humidity_2m:gm3',
'air_density_2m:kgm3', 'ceiling_height_agl:m', 'clear_sky_energy_1h:J',
'clear_sky_rad:W', …]
                ('int', ['bool']) :  2 | ['snow_density:kgm3', 'is_estimated']
        0.1s = Fit runtime
        41 features in original data used to generate 41 features in processed
data.
        Train Data (Processed) Memory Usage: 8.02 MB (0.3% of available memory)
```

```
Data preprocessing and feature engineering runtime = 0.17s …
AutoGluon will gauge predictive performance using evaluation metric:
'mean_absolute_error'
        This metric's sign has been flipped to adhere to being higher_is_better.
The metric score can be multiplied by -1 to get the metric value.
        To change this, specify the eval_metric parameter of Predictor()
use_bag_holdout=True, will use tuning_data as holdout (will not be used for
early stopping).
User-specified model hyperparameters to be fit:
{
        'NN_TORCH': {},
        'GBM': [{'extra_trees': True, 'ag_args': {'name_suffix': 'XT'}}, {},
'GBMLarge'],
        'CAT': {},
        'XGB': {},
        'FASTAI': {},
        'RF': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'XT': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'KNN': [{'weights': 'uniform', 'ag_args': {'name_suffix': 'Unif'}},
{'weights': 'distance', 'ag_args': {'name_suffix': 'Dist'}}],
}
Excluded models: ['CAT', 'XGB', 'RF'] (Specified by `excluded_model_types`)
Fitting 8 L1 models …
Fitting model: KNeighborsUnif_BAG_L1 … Training model for up to 599.83s of the
599.83s of remaining time.
        -19.3805         = Validation score   (-mean_absolute_error)
        0.02s    = Training   runtime
        84.7s    = Validation runtime
Fitting model: KNeighborsDist_BAG_L1 … Training model for up to 506.64s of the
506.64s of remaining time.
        -19.5178         = Validation score   (-mean_absolute_error)
        0.02s    = Training   runtime
        96.04s   = Validation runtime
Fitting model: LightGBMXT_BAG_L1 … Training model for up to 402.86s of the
402.85s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
SequentialLocalFoldFittingStrategy

[1000]  valid_set's l1: 20.4423
[2000]  valid_set's l1: 19.6976
```

```
[3000]  valid_set's l1: 19.3299
[4000]  valid_set's l1: 19.1266
[5000]  valid_set's l1: 19.0207
        Ran out of time, early stopping on iteration 5810. Best iteration is:
        [5785]  valid_set's l1: 18.9581
[1000]  valid_set's l1: 19.5392
[2000]  valid_set's l1: 18.7641
[3000]  valid_set's l1: 18.4218
[4000]  valid_set's l1: 18.2982
        Ran out of time, early stopping on iteration 4682. Best iteration is:
        [4681]  valid_set's l1: 18.2238
[1000]  valid_set's l1: 19.9367
[2000]  valid_set's l1: 19.4343
[3000]  valid_set's l1: 19.1701
[4000]  valid_set's l1: 18.988
        Ran out of time, early stopping on iteration 4442. Best iteration is:
        [4441]  valid_set's l1: 18.9296
[1000]  valid_set's l1: 19.8456
[2000]  valid_set's l1: 19.1611
[3000]  valid_set's l1: 18.83
        Ran out of time, early stopping on iteration 3493. Best iteration is:
        [3493]  valid_set's l1: 18.7373
[1000]  valid_set's l1: 18.8303
[2000]  valid_set's l1: 18.1495
[3000]  valid_set's l1: 17.7981
[4000]  valid_set's l1: 17.6383
[5000]  valid_set's l1: 17.5538
[6000]  valid_set's l1: 17.456
        Ran out of time, early stopping on iteration 6401. Best iteration is:
        [6384]  valid_set's l1: 17.4308
[1000]  valid_set's l1: 18.8522
[2000]  valid_set's l1: 18.3947
[3000]  valid_set's l1: 18.056
[4000]  valid_set's l1: 17.9002
        Ran out of time, early stopping on iteration 4233. Best iteration is:
        [4206]  valid_set's l1: 17.8586
[1000]  valid_set's l1: 19.7356
[2000]  valid_set's l1: 19.1368
[3000]  valid_set's l1: 18.8649
        Ran out of time, early stopping on iteration 3518. Best iteration is:
        [3512]  valid_set's l1: 18.7611
```

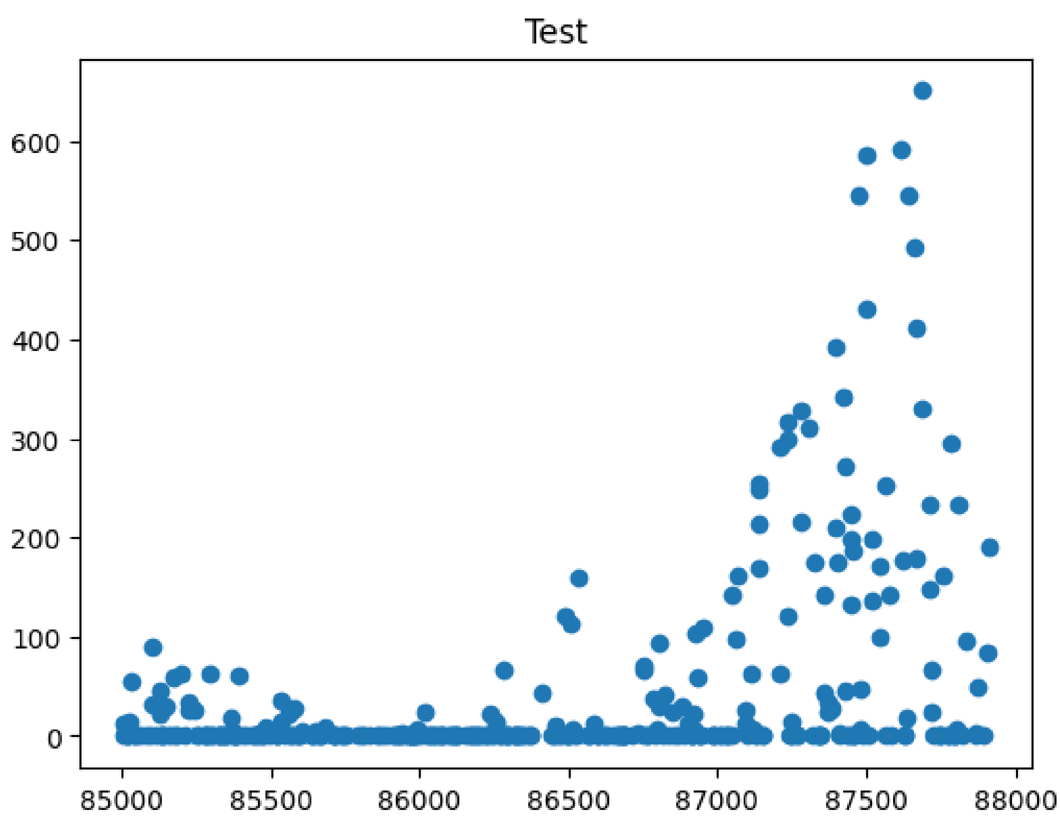
```
[1000]  valid_set's l1: 19.6921
[2000]  valid_set's l1: 19.0326
[3000]  valid_set's l1: 18.6328
[4000]  valid_set's l1: 18.4069
[5000]  valid_set's l1: 18.2786
[6000]  valid_set's l1: 18.1966
[7000]  valid_set's l1: 18.1557
[8000]  valid_set's l1: 18.1209
        Ran out of time, early stopping on iteration 8550. Best iteration is:
        [8521]  valid_set's l1: 18.105
        -11.7588         = Validation score   (-mean_absolute_error)
        384.43s  = Training   runtime
        1.81s    = Validation runtime
Fitting model: LightGBM_BAG_L1 … Training model for up to 13.69s of the 13.68s
of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
SequentialLocalFoldFittingStrategy
        Ran out of time, early stopping on iteration 58. Best iteration is:
        [58]    valid_set's l1: 27.1011
        Ran out of time, early stopping on iteration 80. Best iteration is:
        [80]    valid_set's l1: 22.8612
        Ran out of time, early stopping on iteration 79. Best iteration is:
        [79]    valid_set's l1: 23.7087
        Ran out of time, early stopping on iteration 87. Best iteration is:
        [87]    valid_set's l1: 22.5666
        Ran out of time, early stopping on iteration 84. Best iteration is:
        [84]    valid_set's l1: 22.804
        Ran out of time, early stopping on iteration 103. Best iteration is:
        [103]   valid_set's l1: 21.0775
        Ran out of time, early stopping on iteration 102. Best iteration is:
        [102]   valid_set's l1: 22.6965
        Ran out of time, early stopping on iteration 129. Best iteration is:
        [129]   valid_set's l1: 21.1514
        -18.1958         = Validation score   (-mean_absolute_error)
        13.12s   = Training   runtime
        0.03s    = Validation runtime
Fitting model: ExtraTreesMSE_BAG_L1 … Training model for up to 0.46s of the
0.46s of remaining time.
        -15.6819         = Validation score   (-mean_absolute_error)
        3.1s     = Training   runtime
        0.44s    = Validation runtime
Completed 1/20 k-fold bagging repeats …
Fitting model: WeightedEnsemble_L2 … Training model for up to 360.0s of the
-3.51s of remaining time.
        -11.7568         = Validation score   (-mean_absolute_error)
        0.05s    = Training   runtime
        0.0s     = Validation runtime
```

```
AutoGluon training complete, total runtime = 603.59s … Best model:
"WeightedEnsemble_L2"
TabularPredictor saved. To load, use: predictor =
TabularPredictor.load("AutogluonModels/submission_123_jorge_C/")
Evaluation: mean_absolute_error on test data: -13.096481825131798
        Note: Scores are always higher_is_better. This metric score can be
multiplied by -1 to get the metric value.
Evaluations on test data:
{
    "mean_absolute_error": -13.096481825131798,
    "root_mean_squared_error": -34.23995914165886,
    "mean_squared_error": -1172.374802022468,
    "r2": 0.8864144040338552,
    "pearsonr": 0.952584961559198,
    "median_absolute_error": -0.82662034034729
}

Evaluation on test data:
-13.096481825131798
```




```
                    model  score_test  score_val  pred_time_test  pred_time_val
fit_time  pred_time_test_marginal  pred_time_val_marginal  fit_time_marginal
```

```
stack_level  can_infer  fit_order
0    WeightedEnsemble_L2  -13.096482 -11.756789         1.870625       86.513985
384.506397                 0.001869                   0.000482           0.053767
2        True           6
1      LightGBMXT_BAG_L1  -13.150320 -11.758754         0.541423        1.814085
384.431918                 0.541423                   1.814085         384.431918
1        True           3
2    ExtraTreesMSE_BAG_L1  -17.003587 -15.681893         0.157400        0.436322
3.095096                 0.157400                   0.436322           3.095096
1        True           5
3  KNeighborsDist_BAG_L1  -18.491110 -19.517754         1.457215       96.043076
0.018904                 1.457215                  96.043076           0.018904
1        True           2
4  KNeighborsUnif_BAG_L1  -18.537639 -19.380456         1.327333       84.699418
0.020712                 1.327333                  84.699418           0.020712
1        True           1
5        LightGBM_BAG_L1  -20.982739 -18.195840         0.017541        0.029602
13.117195                 0.017541                   0.029602          13.117195
1        True           4
```



[70]:
```
# save leaderboards to csv
pd.concat(leaderboards).to_csv(f"leaderboards/{new_filename}.csv")


for i in range(len(predictors)):
    print(f"Predictor {i}:")
    print(predictors[i].
 ↪info()["model_info"]["WeightedEnsemble_L2"]["children_info"]["S1F1"]["model_weights"])
```

```
Predictor 0:
{'LightGBMXT_BAG_L1': 1.0}
Predictor 1:
{'LightGBMXT_BAG_L1': 0.8481012658227848, 'ExtraTreesMSE_BAG_L1':
0.1518987341772152}
Predictor 2:
{'KNeighborsUnif_BAG_L1': 0.015873015873015872, 'LightGBMXT_BAG_L1':
0.9841269841269841}
```

## 5 Submit

[71]:
```
import pandas as pd
import matplotlib.pyplot as plt

future_test_data = TabularDataset('X_test_raw.csv')
future_test_data["ds"] = pd.to_datetime(future_test_data["ds"])
#test_data
```

```
Loaded data from: X_test_raw.csv | Columns = 45 / 45 | Rows = 4608 -> 4608
```

[72]:
```
test_ids = TabularDataset('test.csv')
test_ids["time"] = pd.to_datetime(test_ids["time"])
# merge test_data with test_ids
future_test_data_merged = pd.merge(future_test_data, test_ids, how="inner",␣
 ↪right_on=["time", "location"], left_on=["ds", "location"])

#test_data_merged
```

```
Loaded data from: test.csv | Columns = 4 / 4 | Rows = 2160 -> 2160
```

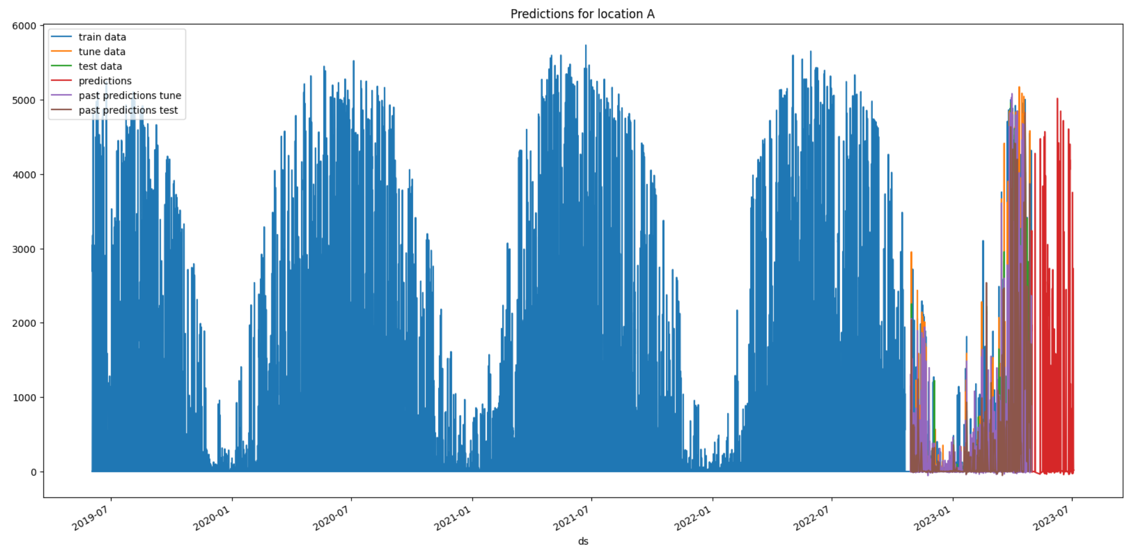
[73]:
```
# predict, grouped by location
predictions = []
location_map = {
    "A": 0,
    "B": 1,
    "C": 2
}
for loc, group in future_test_data.groupby('location'):
    i = location_map[loc]
```

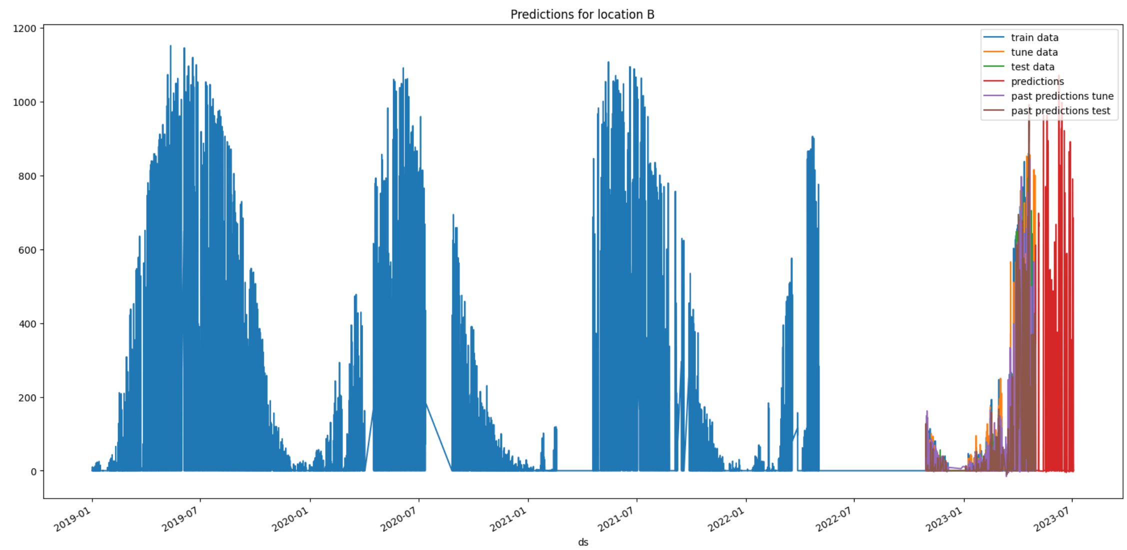
```
    subset = future_test_data_merged[future_test_data_merged["location"] ==␣
↪loc].reset_index(drop=True)
    #print(subset)
    pred = predictors[i].predict(subset)
    subset["prediction"] = pred
    predictions.append(subset)

    # get past predictions
    #train_data.loc[train_data["location"] == loc, "prediction"] = ␣
↪predictors[i].predict(train_data[train_data["location"] == loc])
    if use_tune_data:
        tuning_data.loc[tuning_data["location"] == loc, "prediction"] = ␣
↪predictors[i].predict(tuning_data[tuning_data["location"] == loc])
    if use_test_data:
        test_data.loc[test_data["location"] == loc, "prediction"] = ␣
↪predictors[i].predict(test_data[test_data["location"] == loc])
```

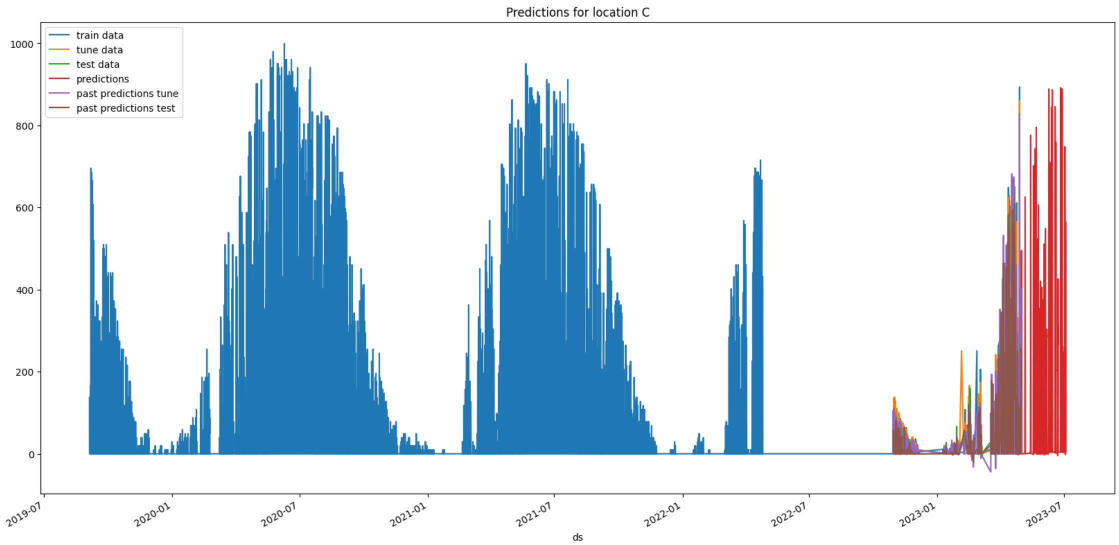
[74]:

```
# plot predictions for location A, in addition to train data for A
for loc, idx in location_map.items():
    fig, ax = plt.subplots(figsize=(20, 10))
    # plot train data
    train_data[train_data["location"]==loc].plot(x='ds', y='y', ax=ax,␣
↪label="train data")
    if use_tune_data:
        tuning_data[tuning_data["location"]==loc].plot(x='ds', y='y', ax=ax,␣
↪label="tune data")
    if use_test_data:
        test_data[test_data["location"]==loc].plot(x='ds', y='y', ax=ax,␣
↪label="test data")

    # plot predictions
    predictions[idx].plot(x='ds', y='prediction', ax=ax, label="predictions")

    # plot past predictions
    #train_data_with_dates[train_data_with_dates["location"]==loc].plot(x='ds',␣
↪y='prediction', ax=ax, label="past predictions")
    #train_data[train_data["location"]==loc].plot(x='ds', y='prediction',␣
↪ax=ax, label="past predictions train")
    if use_tune_data:
        tuning_data[tuning_data["location"]==loc].plot(x='ds', y='prediction',␣
↪ax=ax, label="past predictions tune")
    if use_test_data:
        test_data[test_data["location"]==loc].plot(x='ds', y='prediction',␣
↪ax=ax, label="past predictions test")
```

```python
# title
ax.set_title(f"Predictions for location {loc}")
```






[75]:
```
temp_predictions = [prediction.copy() for prediction in predictions]
if clip_predictions:
    # clip predictions smaller than 0 to 0
    for pred in temp_predictions:
        # print smallest prediction
        print("Smallest prediction:", pred["prediction"].min())
        pred.loc[pred["prediction"] < 0, "prediction"] = 0
        print("Smallest prediction after clipping:", pred["prediction"].min())

# Instead of clipping, shift all prediction values up by the largest negative␣
 ↪number.
# This way, the smallest prediction will be 0.
elif shift_predictions:
    for pred in temp_predictions:
        # print smallest prediction
        print("Smallest prediction:", pred["prediction"].min())
        pred["prediction"] = pred["prediction"] - pred["prediction"].min()
        print("Smallest prediction after clipping:", pred["prediction"].min())

elif shift_predictions_by_average_of_negatives_then_clip:
    for pred in temp_predictions:
        # print smallest prediction
        print("Smallest prediction:", pred["prediction"].min())
        mean_negative = pred[pred["prediction"] < 0]["prediction"].mean()
        # if not nan
        if mean_negative == mean_negative:
            pred["prediction"] = pred["prediction"] - mean_negative
```

```
        pred.loc[pred["prediction"] < 0, "prediction"] = 0
        print("Smallest prediction after clipping:", pred["prediction"].min())



# concatenate predictions
submissions_df = pd.concat(temp_predictions)
submissions_df = submissions_df[["id", "prediction"]]
submissions_df
```

```
Smallest prediction: -41.899334
Smallest prediction after clipping: 0.0
Smallest prediction: -4.4888353
Smallest prediction after clipping: 0.0
Smallest prediction: -4.3920894
Smallest prediction after clipping: 0.0
```

[75]:

```
       id  prediction
0       0    0.000000
1       1    0.000000
2       2    0.000000
3       3   45.446655
4       4  262.431946
..    …         …
715  2155   70.653954
716  2156   45.066662
717  2157   11.451385
718  2158    4.537232
719  2159    4.065796

[2160 rows x 2 columns]
```

[76]:

```
# Save the submission DataFrame to submissions folder, create new name based on␣
 ↪last submission, format is submission_<last_submission_number + 1>.csv

# Save the submission
print(f"Saving submission to submissions/{new_filename}.csv")
submissions_df.to_csv(os.path.join('submissions', f"{new_filename}.csv"),␣
 ↪index=False)
print("jall1a")
```

```
Saving submission to submissions/submission_123_jorge.csv
jall1a
```

[77]:

```
# feature importance
# print starting calculating feature importance for location A with big text␣
 ↪font
```

```
print("\033[1m" + "Calculating feature importance for location A..." +
 ↪"\033[0m")
predictors[0].feature_importance(feature_stage="original",
 ↪data=test_data[test_data["location"] == "A"], time_limit=60*10)
print("\033[1m" + "Calculating feature importance for location B..." +
 ↪"\033[0m")
predictors[1].feature_importance(feature_stage="original",
 ↪data=test_data[test_data["location"] == "B"], time_limit=60*10)
print("\033[1m" + "Calculating feature importance for location C..." +
 ↪"\033[0m")
predictors[2].feature_importance(feature_stage="original",
 ↪data=test_data[test_data["location"] == "C"], time_limit=60*10)
```

```
These features in provided data are not utilized by the predictor and will be
ignored: ['ds', 'elevation:m', 'snow_drift:idx', 'location', 'prediction']
Computing feature importance via permutation shuffling for 41 features using 376
rows with 10 shuffle sets… Time limit: 600s…
```

**Calculating feature importance for location A…**

```
        270.44s = Expected runtime (27.04s per shuffle set)
        103.13s = Actual runtime (Completed 10 of 10 shuffle sets)
These features in provided data are not utilized by the predictor and will be
ignored: ['ds', 'elevation:m', 'location', 'prediction']
Computing feature importance via permutation shuffling for 42 features using 376
rows with 10 shuffle sets… Time limit: 600s…
```

**Calculating feature importance for location B…**

```
        409.32s = Expected runtime (40.93s per shuffle set)
```

```
---------------------------------------------------------------------------
KeyboardInterrupt                         Traceback (most recent call last)
/Users/jorgensandhaug/Desktop/tdt4173/TDT4173/autogluon_each_location.ipynb Cell
 ↪37 line 6
      <a href='vscode-notebook-cell:/Users/jorgensandhaug/Desktop/tdt4173/
 ↪TDT4173/autogluon_each_location.ipynb#Y225sZmlsZQ%3D%3D?line=3'>4</a>
 ↪predictors[0].feature_importance(feature_stage="original",
 ↪data=test_data[test_data["location"] == "A"], time_limit=60*10)
      <a href='vscode-notebook-cell:/Users/jorgensandhaug/Desktop/tdt4173/
 ↪TDT4173/autogluon_each_location.ipynb#Y225sZmlsZQ%3D%3D?line=4'>5</a>
 ↪print("\033[1m" + "Calculating feature importance for location B…" + "\033[0m")
----> <a href='vscode-notebook-cell:/Users/jorgensandhaug/Desktop/tdt4173/
 ↪TDT4173/autogluon_each_location.ipynb#Y225sZmlsZQ%3D%3D?line=5'>6</a>
 ↪predictors[1].feature_importance(feature_stage="original",
 ↪data=test_data[test_data["location"] == "B"], time_limit=60*10)
      <a href='vscode-notebook-cell:/Users/jorgensandhaug/Desktop/tdt4173/
 ↪TDT4173/autogluon_each_location.ipynb#Y225sZmlsZQ%3D%3D?line=6'>7</a>
 ↪print("\033[1m" + "Calculating feature importance for location C…" + "\033[0m")
```

```
     <a href='vscode-notebook-cell:/Users/jorgensandhaug/Desktop/tdt4173/
 ↪TDT4173/autogluon_each_location.ipynb#Y225sZmlsZQ%3D%3D?line=7'>8</a>␣
 ↪predictors[2].feature_importance(feature_stage="original",␣
 ↪data=test_data[test_data["location"] == "C"], time_limit=60*10)

File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/site-packages/autogluon/
 ↪tabular/predictor/predictor.py:2425, in TabularPredictor.
 ↪feature_importance(self, data, model, features, feature_stage, subsample_size,␣
 ↪time_limit, num_shuffle_sets, include_confidence_band, confidence_level,␣
 ↪silent)
   2422 if num_shuffle_sets is None:
   2423     num_shuffle_sets = 10 if time_limit else 5
-> 2425 fi_df = self._learner.get_feature_importance(
   2426     model=model,
   2427     X=data,
   2428     features=features,
   2429     feature_stage=feature_stage,
   2430     subsample_size=subsample_size,
   2431     time_limit=time_limit,
   2432     num_shuffle_sets=num_shuffle_sets,
   2433     silent=silent,
   2434 )
   2436 if include_confidence_band:
   2437     if confidence_level <= 0.5 or confidence_level >= 1.0:

File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/site-packages/autogluon/
 ↪tabular/learner/abstract_learner.py:870, in AbstractTabularLearner.
 ↪get_feature_importance(self, model, X, y, features, feature_stage,␣
 ↪subsample_size, silent, **kwargs)
    867         X = X.drop(columns=unused_features)
    869     if feature_stage == "original":
--> 870         return trainer._get_feature_importance_raw(
    871             model=model, X=X, y=y, features=features,␣
 ↪subsample_size=subsample_size, transform_func=self.transform_features,␣
 ↪silent=silent, **kwargs
    872         )
    873     X = self.transform_features(X)
    874 else:

File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/site-packages/autogluon/core/
 ↪trainer/abstract_trainer.py:2574, in AbstractTrainer.
 ↪_get_feature_importance_raw(self, X, y, model, eval_metric, **kwargs)
   2572 model: AbstractModel = self.load_model(model)
   2573 predict_func_kwargs = dict(model=model)
-> 2574 return compute_permutation_feature_importance(
   2575     X=X,
   2576     y=y,
   2577     predict_func=predict_func,
   2578     predict_func_kwargs=predict_func_kwargs,
   2579     eval_metric=eval_metric,
```

```
   2580     quantile_levels=self.quantile_levels,
   2581     **kwargs,
   2582 )

File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/site-packages/autogluon/core/
 ↪utils/utils.py:867, in compute_permutation_feature_importance(X, y,␣
 ↪predict_func, eval_metric, features, subsample_size, num_shuffle_sets,␣
 ↪predict_func_kwargs, transform_func, transform_func_kwargs, time_limit,␣
 ↪silent, log_prefix, importance_as_list, random_state, **kwargs)
    865 else:
    866     X_raw_transformed = X_raw if transform_func is None else␣
 ↪transform_func(X_raw, **transform_func_kwargs)
--> 867 y_pred = predict_func(X_raw_transformed, **predict_func_kwargs)
    869 row_index = 0
    870 for feature in parallel_computed_features:

File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/site-packages/autogluon/core/
 ↪trainer/abstract_trainer.py:749, in AbstractTrainer.predict(self, X, model)
    747     model = self._get_best()
    748 cascade = isinstance(model, list)
--> 749 return self._predict_model(X, model, cascade=cascade)

File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/site-packages/autogluon/core/
 ↪trainer/abstract_trainer.py:2388, in AbstractTrainer._predict_model(self, X,␣
 ↪model, model_pred_proba_dict, cascade)
   2387 def _predict_model(self, X, model, model_pred_proba_dict=None,␣
 ↪cascade=False):
-> 2388     y_pred_proba = self._predict_proba_model(X=X, model=model,␣
 ↪model_pred_proba_dict=model_pred_proba_dict, cascade=cascade)
   2389     return get_pred_from_proba(y_pred_proba=y_pred_proba,␣
 ↪problem_type=self.problem_type)

File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/site-packages/autogluon/core/
 ↪trainer/abstract_trainer.py:2392, in AbstractTrainer.
 ↪_predict_proba_model(self, X, model, model_pred_proba_dict, cascade)
   2391 def _predict_proba_model(self, X, model, model_pred_proba_dict=None,␣
 ↪cascade=False):
-> 2392     return self.get_pred_proba_from_model(model=model, X=X,␣
 ↪model_pred_proba_dict=model_pred_proba_dict, cascade=cascade)

File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/site-packages/autogluon/core/
 ↪trainer/abstract_trainer.py:769, in AbstractTrainer.
 ↪get_pred_proba_from_model(self, model, X, model_pred_proba_dict, cascade)
    767 else:
    768     models = [model]
--> 769 model_pred_proba_dict = self.get_model_pred_proba_dict(X=X,␣
 ↪models=models, model_pred_proba_dict=model_pred_proba_dict, cascade=cascade)
    770 if not isinstance(model, str):
    771     model = model.name
```

```
File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/site-packages/autogluon/core/
↪trainer/abstract_trainer.py:1018, in AbstractTrainer.
↪get_model_pred_proba_dict(self, X, models, model_pred_proba_dict,␣
↪model_pred_time_dict, record_pred_time, use_val_cache, cascade,␣
↪cascade_threshold)
   1016     else:
   1017         preprocess_kwargs = dict(infer=False,␣
↪model_pred_proba_dict=model_pred_proba_dict)
-> 1018     model_pred_proba_dict[model_name] = model.predict_proba(X,␣
↪**preprocess_kwargs)
   1019 else:
   1020     model_pred_proba_dict[model_name] = model.predict_proba(X)

File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/site-packages/autogluon/core/
↪models/ensemble/bagged_ensemble_model.py:346, in BaggedEnsembleModel.
↪predict_proba(self, X, normalize, **kwargs)
    344 model = self.load_child(self.models[0])
    345 X = self.preprocess(X, model=model, **kwargs)
--> 346 pred_proba = model.predict_proba(X=X, preprocess_nonadaptive=False,␣
↪normalize=normalize)
    347 for model in self.models[1:]:
    348     model = self.load_child(model)

File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/site-packages/autogluon/core/
↪models/abstract/abstract_model.py:931, in AbstractModel.predict_proba(self, X,␣
↪normalize, **kwargs)
    929 if normalize is None:
    930     normalize = self.normalize_pred_probas
--> 931 y_pred_proba = self._predict_proba(X=X, **kwargs)
    932 if normalize:
    933     y_pred_proba = normalize_pred_probas(y_pred_proba, self.problem_type)

File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/site-packages/autogluon/
↪tabular/models/lgb/lgb_model.py:234, in LGBModel._predict_proba(self, X,␣
↪num_cpus, **kwargs)
    231 def _predict_proba(self, X, num_cpus=0, **kwargs):
    232     X = self.preprocess(X, **kwargs)
--> 234     y_pred_proba = self.model.predict(X, num_threads=num_cpus)
    235     if self.problem_type == REGRESSION:
    236         return y_pred_proba

File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/site-packages/lightgbm/basic.
↪py:3538, in Booster.predict(self, data, start_iteration, num_iteration,␣
↪raw_score, pred_leaf, pred_contrib, data_has_header, is_reshape, **kwargs)
   3536     else:
   3537         num_iteration = -1
-> 3538 return predictor.predict(data, start_iteration, num_iteration,
   3539                          raw_score, pred_leaf, pred_contrib,
```

```
   3540                                 data_has_header, is_reshape)

File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/site-packages/lightgbm/basic.py:848, in _InnerPredictor.predict(self, data, start_iteration, num_iteration, raw_score, pred_leaf, pred_contrib, data_has_header, is_reshape)
    846     preds, nrow = self.__pred_for_csc(data, start_iteration, num_iteration, predict_type)
    847 elif isinstance(data, np.ndarray):
--> 848     preds, nrow = self.__pred_for_np2d(data, start_iteration, num_iteration, predict_type)
    849 elif isinstance(data, list):
    850     try:

File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/site-packages/lightgbm/basic.py:938, in _InnerPredictor.__pred_for_np2d(self, mat, start_iteration, num_iteration, predict_type)
    936     return preds, nrow
    937 else:
--> 938     return inner_predict(mat, start_iteration, num_iteration, predict_type)

File /opt/homebrew/anaconda3/envs/ag/lib/python3.10/site-packages/lightgbm/basic.py:908, in _InnerPredictor.__pred_for_np2d.<locals>.inner_predict(mat, start_iteration, num_iteration, predict_type, preds)
    906     raise ValueError("Wrong length of pre-allocated predict array")
    907 out_num_preds = ctypes.c_int64(0)
--> 908 _safe_call(_LIB.LGBM_BoosterPredictForMat(
    909     self.handle,
    910     ptr_data,
    911     ctypes.c_int(type_ptr_data),
    912     ctypes.c_int32(mat.shape[0]),
    913     ctypes.c_int32(mat.shape[1]),
    914     ctypes.c_int(C_API_IS_ROW_MAJOR),
    915     ctypes.c_int(predict_type),
    916     ctypes.c_int(start_iteration),
    917     ctypes.c_int(num_iteration),
    918     c_str(self.pred_parameter),
    919     ctypes.byref(out_num_preds),
    920     preds.ctypes.data_as(ctypes.POINTER(ctypes.c_double))))
    921 if n_preds != out_num_preds.value:
    922     raise ValueError("Wrong length for predict results")

KeyboardInterrupt:
```

[ ]:

```python
# save this notebook to submissions folder
import subprocess
import os
```

```
#subprocess.run(["jupyter", "nbconvert", "--to", "pdf", "--output", os.path.
↪join('notebook_pdfs', f"{new_filename}_automatic_save.pdf"),␣
↪"autogluon_each_location.ipynb"])
subprocess.run(["jupyter", "nbconvert", "--to", "pdf", "--output", os.path.
↪join('notebook_pdfs', f"{new_filename}.pdf"), "autogluon_each_location.
↪ipynb"])
```

[ ]:
```
# import subprocess

# def execute_git_command(directory, command):
#     """Execute a Git command in the specified directory."""
#     try:
#         result = subprocess.check_output(['git', '-C', directory] + command,␣
↪stderr=subprocess.STDOUT)
#         return result.decode('utf-8').strip(), True
#     except subprocess.CalledProcessError as e:
#         print(f"Git command failed with message: {e.output.decode('utf-8').
↪strip()}")
#         return e.output.decode('utf-8').strip(), False

# git_repo_path = "."

# execute_git_command(git_repo_path, ['config', 'user.email',␣
↪'henrikskog01@gmail.com'])
# execute_git_command(git_repo_path, ['config', 'user.name', hello if hello is␣
↪not None else 'Henrik eller Jørgen'])

# branch_name = new_filename

# # add datetime to branch name
# branch_name += f"_{pd.Timestamp.now().strftime('%Y-%m-%d_%H-%M-%S')}"

# commit_msg = "run result"

# execute_git_command(git_repo_path, ['checkout', '-b',branch_name])

# # Navigate to your repo and commit changes
# execute_git_command(git_repo_path, ['add', '.'])
# execute_git_command(git_repo_path, ['commit', '-m',commit_msg])

# # Push to remote
# output, success = execute_git_command(git_repo_path, ['push',␣
↪'origin',branch_name])

# # If the push fails, try setting an upstream branch and push again
# if not success and 'upstream' in output:
#     print("Attempting to set upstream and push again...")
```

```
#     execute_git_command(git_repo_path, ['push', '--set-upstream',␣
↪'origin',branch_name])
#     execute_git_command(git_repo_path, ['push', 'origin', 'henrik_branch'])

# execute_git_command(git_repo_path, ['checkout', 'main'])
```

[ ]:

```

```